THE UNIVERSITY *of* EDINBURGH

Studies on Social Learning and on Motivated Beliefs: Theory and Evidence

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Abstract

This thesis contains four chapters presenting theory and empirical evidence for two distinct aspects of human behaviour: social learning and motivated beliefs.

I develop a simple theory to revisit the classical social learning models by challenging the assumption of freely available information. My model suggests that when it is costly to acquire information, social learning (herding) is prevalent, and people do not have incentives to acquire private information (e.g. to form their own judgements). Classical information cascade models suggest that although herding is observed, information aggregation is still possible with communication channels (e.g. a survey); however, my model indicates that information aggregation is unattainable because people in the herd do not acquire private information.

We then test my model in a laboratory and find that, as predicted, subjects can learn from others successfully. Also, individual heterogeneity exists in: there are herd animals biased against private information, lone wolves who are biased toward it and subjects who behave optimally. In aggregate, there is no overall bias for or against private information. We also document a new cognitive bias involved in processing social information. Individual characteristics, especially the cognitive ability, seems to be a very good indicator of subjects' behaviour. Subjects with higher cognitive scores choose optimal information more frequently and follow information more frequently.

Overconfidence can be driven by the consumption motive (e.g. savouring future payoff/self-image) and the instrumental motive (e.g. being optimistic about the outcome of effort for motivation). I develop a simple model incorporating these two motives and suggest that individuals hold a dynamic pattern of overconfidence.

Then I conduct an online field experiment with students to test the theory. The experimental findings indicate that students are likely to adopt overconfident beliefs as a commitment device to deal with their self-control problem. However, I do not find evidence for the consumption motive of overconfidence.

Lay Summary

Economists believe that following others is often beneficial because one can learn valuable information from other people's behaviour. Those models often assume that people have personal judgement, and can observe the actions of their neighbour with no costs. I believe that this assumption is not realistic in many cases. Therefore, I develop a simple social learning model in which information acquisition is costly. My model indicates that information aggregation often fails because people have no incentive to form a personal judgement. In other words, the possibility of learning from others prohibits people producing original ideas.

We then test the above model in a lab. We design an experiment in a computer-based laboratory and recruit 128 human subjects. Subjects are incentivised to choose the optimal information helping them to make the optimal decision. Our experimental findings suggest that people can anticipate the information value embedded in other people's actions. Although on average people are not biased towards private information, individual heterogeneity presents. About 10% of our subjects never choose to observe other people's actions even when it is optimal to do so. Another 10%, on the contrary, always engage in social learning regardless of the situation. Finally, we find individual characteristics, such as cognitive ability and personality, can explain social learning behaviour.

The second topic I present in this thesis is motivated beliefs, specifically, overconfidence. Economists believe that economic motivations drive people to hold overconfident beliefs. The first motivation is the consumption value of overconfidence that people feel happy to hold positive views about themselves. Another motivation is to deal with self-control problem. By holding overconfident beliefs about the outcome of efforts, people may exert more efforts in the face of the self-control problem (e.g. study more, save more, etc.). Based on earlier models, I produce a simple model explaining the dynamics of students' confidence level. I also conduct an online field experiment to collect students' confidence level data. My experiment suggests that students use overconfident beliefs as a tool to deal with their self-control problems.

Dedication

To my grandmother Shujiao Liu, and to the memory of my grandfather Heichou Ma, I take your lessons with me, every day.

Declaration

I declare that this thesis was written and composed by myself and is the result of my own work unless clearly stated and referenced. Chapter 3 of this thesis is co-authored with John Duffy of the University of California, Irvine, Ed Hopkins of the University of Edinburgh and Tatiana Kornienko of the University of Edinburgh. I am the corresponding author and made substantial contributions to the experimental design and data analysis. This thesis has not been submitted for any other degree or professional qualifications.

Signature:

Date:

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CHAPTER 1 INTRODUCTION

Human beings are social animals, and the social aspect of people has been addressed in many fields of research, including biology, psychology and economics. Since Banerjee (1992) and Bikhchandani et al. (1992), there is a growing literature on social learning (herding) to study why and how are people learning from others.[1] Many real life examples are a result of herding, such as bank runs, financial market bubbles, fashions and social trends. One common assumption adopted by earlier social learning models is that individuals have access to informative private information with no costs. In reality, forming a reasonable personal judgement is often costly in terms of time, money, effort and attention. The same cost argument applies to the public information: it can also be costly to observe other people's behaviour.

To address this issue, I develop a simple model with costly information acquisition in chapter 2 of this thesis. This model focuses on the information acquisition aspect of social learning. Consistent with the classical models, information cascades are predicted. In contrast to the classical social learning models where information cascades form stochastically, my model predicts that information cascade starts deterministically at the fourth agent in a sequence. Also, in contrast to the classical models, my model indicates that even if communication channels are available, "the wisdom of the crowd" (information aggregation) is unattainable because agents in the cascade do not have strict incentives to acquire private information.

The experimental evidence on social learning is abundant. However, since many of these experiments are driven by the models of Banerjee (1992) and Bikhchandani et al. (1992) and the design of Anderson & Holt (1997), subjects in the experiment are given both private and public information. In such settings, social learning problem is reduced to an information interpretation problem: to what degree one should follow the public. However, in reality (and consistent with the model presented in chapter 2), before interpreting information, an individual often has to acquire the relevant information at the first place. Therefore, the external validity of the conclusion from existing experiments that people overweight their private information (for a meta-analysis see, Weizsäcker, 2010) is limited because the in-

[1] Notable theoretical papers include and not limited to L. Smith & Sørensen (2000); Banerjee & Fudenberg (2004); Acemoglu et al. (2010); Guarino et al. (2011); Guarino & Jehiel (2013). For experimental papers, see for example, Anderson & Holt (1997), Hung & Plott (2001) and Weizsäcker (2010).

formation acquisition aspect of social learning is ignored. In chapter 3, we report a social learning experiment designed to identify bias in information acquisition. In contrast to the standard sequential social learning experimental design where subjects are given both private and social information prior to guessing an unknown binary state of the world, in our experiment, subjects must instead choose between receiving a private signal or seeing the guesses made by previous subjects in the sequence (i.e., social information). By requiring our subjects to make this choice at different points in the sequence, our within-subject design allows us to separate biased from optimal information choices. We find heterogeneity in bias, with some subjects consistently choosing social information when private information is optimal and vice-versa. We also find that subjects' programme of study, individual traits and cognitive ability can explain the extent of bias in their information choices. We also document that subjects exhibit efficiency concerns in longer sequences, associated with increased use of private signals.

The first part of this thesis addresses issues on the social and interpersonal aspects of human behaviour, while in the second part, I focus on the behavioural bias from the intrapersonal perspective. Specifically, I study the intrapersonal motives of overconfidence. In chapter 4, I develop a model of motivated overconfidence based on (Bénabou & Tirole, 2002, 2016). Consistent with the previous models, both consumption motive and instrumental motive present, and lead to overconfident beliefs. On the other hand, my model contains two key features differing from the literature. First, I introduce a waiting stage where the agent is no longer able to change the already exerted effort level but still needs to wait for result realisation. Second, I propose a quadratic cost for distorting beliefs, and thus, it is increasingly more costly for people to hold more extreme beliefs. Consequently, this model predicts that the agent holds a dynamic pattern of overconfident belief changes over time. Agents start with high expectations to counteract the present temptation, and to savour the positive feelings; Then beliefs drop but still overconfident during the waiting stage for anticipatory purpose before dropping down to its lowest level at the realisation stage.

Then I test my motivated overconfidence model through an online field study, and the results are presented in chapter 5. The study is conducted with undergraduate students from two core economics courses who are required to submit a coursework essay. With the help of the online teaching system "Blackboard Learn", I collect students' beliefs about their essay performance multiple times through a series of online surveys. Although students are not overconfident, I find a clear dynamic pattern of students' confidence level. Specifically, they are most optimistic about their essays while working on it, and become much less confident after the submission of the essay, with their confidence level remaining unchanged until the release of essay marks. The dynamics of the confidence level are consistent with a possibility that students adopt inflated beliefs as a motivator to pursue difficult goals, providing an experimental support for the instrumental motive of overconfidence. In contrast, the consumption motive hypothesis is not supported by the data.

CHAPTER 2 A MODEL OF SEQUENTIAL SOCIAL LEARNING WITH INFORMATION CHOICE

2.1 Introduction

Human beings are social animals and the social aspect of the human race has been addressed in many fields of research, including biology, psychology and economics. Herd behaviour (or uniform social behaviour) has been heavily discussed by economists since the two seminal papers by Banerjee (1992) and Bikhchandani et al. (1992). The main insight of this theoretical literature is that herd behaviour/information cascade can be a rational response to the information contained in the actions of others. Many real life examples can be described as the phenomena of herding, such as bank runs, financial market bubbles, fashions and social trends.

The existing models assume that each agent has an informative private signal and at the same time can observe her predecessors' decisions with no cost[1]. Arguably, in reality, neither social nor private information is freely available. Information acquisition costs are in terms of money, attention, time, effort and so on. With costly information acquisition, rational agents may acquire either social or private information, but not both.[2] In our model, agents have to choose which information to observe rather than having free access to both private and social information. Existing studies emphasis on the interpretation aspect of social learning–*after* observing both private and social information, how agents update their beliefs. However, interpretation of information is not the entire story since interpretation is conditional on information acquisition. Our model completes the theoretical literature by emphasizing the importance of information acquisition in social learning when information is costly.

The outline of the present model can be illustrated with the following example. Suppose a student has to choose between two optional courses A and B. Suppose she has no prior information about which course will equip her with more valuable skills. A student can acquire information through two channels. First, she could

[1]One notable exception is Song (2016). In his model, private information is freely available and social information can be endogenously acquired.

[2]Even in cases where information is freely available, people may choose to avoid information due to several psychological factors such as ostrich effect (Karlsson et al., 2009), choking under pressure (Dohmen, 2008) and disappointment aversion (Andries & Haddad, 2014).

search for private information by reading the syllabus, textbooks, past papers, the website of course coordinator and so on. Second, she could acquire social information by observing what did her peers choose. Of course, she may decide to obtain both types of information, however, given information acquisitions are costly in terms of time and effort, in many cases, she may choose only one source of information. In such cases, either private or social information can be optimal depending on the specific contexts. For example, the private channel is optimal if the courses are offered for the first time or social observation is difficult and the social channel is optimal when credible historical information about the decisions made by other students is available.

The formal set up of this model is based on the classical social learning models. There is an underlying binary state of the world. A finite number of agents sequentially make a binary decision with the goal of matching the true state. Before making the above decision, each agent chooses between (1) receiving a private informative but imperfect signal regarding the true state and (2) observing the binary decisions made by all her predecessors but *not* their information choices.

Consistent with classical models, this model predicts the formation of information cascades and the failure of asymptotic learning.[3] On the other hand, rather than a stochastic formation of information cascades in classical models, cascades form deterministically in this model. Another distinction is that the "wisdom of the crowd" is unattainable even if communication channels in the present model since agents in a cascade do not have strict incentive to acquire private information. In the classical models, people follow others but each individual holds an informative and independent signal. Consequently, if communication channels (e.g. a survey) are available, information aggregation is still possible. However, in my model, because acquiring information is costly, people in equilibrium do not have incentives to form their own judgement, they simply follow their predecessors. This result challenges the validity of social surveys.

2.2 Literature Review

The idea of informational cascades is firstly proposed to explain social herding by Bikhchandani et al. (1992). In their paper, an informational cascade forms when agents rationally ignore their own information and imitate the behaviour of other agents, for the reason that others might be better informed. In their paper, a

[3]Asymptotic learning refers to the convergence in probability to the correct action as the size of a social network grows (Acemoglu et al., 2011).

real-world journal submission example is given. The referees read the submitted paper, assess its quality, and make the decision. Suppose a referee at a second journal knows that the paper was previously rejected by the first journal. Under the assumption that the referee cannot assess the paper's quality perfectly, the prior rejection tends to favour another rejection. The same logic goes on to the subsequent referees: if it is known that a paper has been rejected by so many previous journals, the chance of future rejection would be high. This idea is modelled mathematically in a relatively general setting with sequential choices, and it can be shown that at some point an agent will rationally ignore her own private information and simply follow the social information – the information accumulated from previous decisions. Once this particular point is reached, an informational cascade forms and all subsequent decisions become uninformative since no private information is revealed. However, information cascade is fragile because, in equilibrium, individuals may rapidly converge on one decision based on little information. As a result, behaviour in cascades is fragile with respect to small shocks–fragility arises systematically.

Banerjee (1992) adopts a very similar theoretical model towards this issue. In his paper, the term "herd behaviour" is used to describe the situation when people are imitating others with the belief that social behaviour may reflect valuable information. The mathematical model in Banerjee (1992) is extremely simplified and very close to the discrete choice model introduced by Bikhchandani et al. (1992).[4] Banerjee (1992) focused on the welfare aspect of such herding. When agents in the sequence ignore their private information and imitate their predecessors, a negative "herd externality" is imposed on the rest of the population. This negative externality comes from the fact that if those herding agents had followed their private information, their decisions would have provided additional information to the rest of the sequence. Therefore, the existence of informational externalities causes a loss of social welfare. Hence the society might be better off if the early agents in the sequence are not allowed to observe the choices made by their predecessors (thus they have to rely on their own information). It leads to an interesting conclusion: "destroying information can be socially beneficial" (Banerjee, 1992, p. 811).

L. Smith & Sørensen (2000) develop a model of agents with heterogeneous preference, and find that herding is not the only possible long run outcome. "Con-

[4]Although the choice variable is continuous in Banerjee (1992), under his maintained assumptions it shares the properties of a discrete choice model.

founded learning"–an informational pooling equilibrium where social history is not informative for anyone may occur in their model. In that case, beliefs converge to a limit point and history offers no decisive information for any agent. And thus each types actions forever split between two actions. L. Smith & Sørensen (2000) also emphasise the difference between informational cascades and herd behaviour. They argue that informational cascades occur when, after some finite time, all agents completely ignore their private information, while herd behaviour occurs when all agents make the same decision but not necessarily ignoring their private information. In other words, in a herding situation, agents choose the same decision, but they may have behaved differently if the realisation of their own private signals had been different as they do not ignore their private information completely. While in an informational cascade, agents choose to follow the behaviour of predecessors without regard to private signals since they believe the social information is so strong that no private information can outweigh it and thus they ignore their private information completely. In our paper, we use the term informational cascade to describe the potential social learning process since when agents choose social information, no private signal will be observed (they ignore their private information entirely).

Acemoglu et al. (2010) also model social learning with heterogeneous agents. In their model, agents are of multiple types and the uncertainty of type distribution presents. On the one hand, information is correctly aggregated when preferences of different types are closely aligned. On the other hand, when heterogeneity in preferences is sufficient, asymptotic learning may be distorted due to identification problems where agents cannot learn from the history even in the long run. The failure of information aggregation in Acemoglu et al. (2010) is fundamentally different from classical information cascade models by Bikhchandani et al. (1992) and Banerjee (1992). In Acemoglu et al. (2010), information may fail to aggregate because agents cannot identify the history efficiently with the presence of type distribution uncertainty; while in classical information cascade models, information aggregation fails because the private signal is bounded (not informative enough to utilise compared to social information).

Information cascade models are also challenged by several researchers. Bernheim (1994) proposes a model describing conformity based on social interaction where individuals care about social status. It is an alternative explanation of herding compared to social learning models. Avery & Zemsky (1998) build a theoretical model explaining the herding in the financial market. In their model, the role of the price mechanism is considered in the aggregation of private information within a sequential decision-making economy. When traders have private information on only a single dimension of uncertainty, price adjustments can prevent herding. Gale (1996) challenge the robustness of the formation of informational cascades by questioning the strong assumptions shared by the social learning models such as exogenous timing, discrete timing & choices and the symmetry of equilibrium.

The most closely related paper to ours is Song (2016). In his paper, the observation structure is endogenous that agents can strategically choose to observe the set of actions. Since making observations is costly, the equilibrium outcome depends on the relative strength of private information as compared to cost. His model indicates that asymptotic learning never occurs with endogenous observation structure as agent sometimes chooses not to make any observation.[5] Also, an interesting welfare conclusion suggests that costly observation may entail better learning because costly observation can sometimes reduce herding externality. The main difference between Song (2016) and this study is the availability of private signal. In his paper, private signal is freely available while in our model private signal is, similar to social information, costly and endogenous. The main argument is that in many real life events agents may have no private belief/information/idea about the decision problem.[6]

2.3 The Model

Each of N players faces the same task of guessing the correct state of the world. N players form a sequence, and each player has an exogenously determined position $n \equiv \{1, 2, ..., n, ..., N\}$. Let player n to denote the player with position n. The state of the world, $\theta \in \{0, 1\}$ is binary with equal prior probabilities. Players sequentially make a decision $d_n \in \{0, 1\}$. The payoff is 1 if $d_n = \theta$ and 0 otherwise.

For each player, before making the decision d_n, she can choose one from the following two pieces of information $i_n \in I(n) = \{s_n, h_n\}$. The first is an independently generated private signal $s_n \in S = \{0, 1\}$, with the accuracy of $q \in (0.5, 1)$ $\forall$ s_n. Specifically, $Pr(s_n = 0|\theta = 0) = Pr(s_n = 1|\theta = 1) = q$ and $Pr(s_n = 0|\theta = 1) = Pr(s_n = 1|\theta = 0) = 1-q$ for all players. The second is a com-

[5]This is a contradiction to Acemoglu et al. (2011) where asymptotic learning is possible with exogenous observation structure.

[6]For example, a new mother may have no private signal about which formula is better for her baby. She can acquire private information by reading instructions/tasting/calling helpline etc., but these activities are costly. Therefore I believe the freely available private signal may not be a natural assumption.

plete history of the decisions made by all predecessors h_n. Specifically, h_1 is empty set, $h_2 = \{d_1\}$, $h_3 = \{d_1, d_2\}$, $h_4 = \{d_1, d_2, d_3\}$ and $h_n = \{d_1, d_2, d_3, ..., d_{n-1}\}$. Players can only observe the final decisions of others, not the information chosen by others. We call this second option h_n as social information.

Therefore a player has to solve two problems: first, given her position in a sequence, which of the two pieces of information to choose. And second, after observing the information she chooses, which decision to make. A strategy for player n is thus a pair of two mappings $\mu_n = (\mu_n^i, \mu_n^d)$ where $\mu_n^i : n \to I(n)$ represents information choice at different positions. $\mu_n^d : I(n) \to \{0, 1\}$ represents the final decision. A strategy profile is a sequence of strategies $\mu = \{\mu_1, \mu_2, ..., \mu_N\}$. The sequence of decisions $\{d_n\}$ is a stochastic process. The probability measure generated by this process is P_μ.

2.3.1 Perfect Bayesian Nash Equilibrium

We define μ^* as a pure strategy perfect Bayesian Nash equilibrium (PBNE). Thus μ_n^* maximises the expected payoff of player n given $\mu_{m<n}^*$. Specifically, both two mappings in equilibrium μ_n^{i*} and μ_n^{d*} must be best responses, given $\mu_{m<n}^{i*}$ and $\mu_{m<n}^{d*}$, to $I(n)$ and $\{0, 1\}$ respectively. The second mapping, interpretation of the observed information in our game is straightforward: subjects should follow the information they observe. For the private signal, as it is informative ($q > 0.5$), subjects should follow it. For social information, as all subjects in a sequence face the same true state and are individually incentivised in the same way, participants have the incentive to follow their predecessors. Thus the key question is which information to observe in the first place (μ_n^i). It can be shown formally by the following two equations with equation (2.1) for μ_n^{d*} and (2.2) for μ_n^{i*}. Let $y^*(i_n)$ be the best response final decision given information i_n.

$$y^*(i_n) = \underset{y \in \{0,1\}}{\arg\max} \quad P_{\mu_{m<n}^*}(y = \theta | i_n) \tag{2.1}$$

Where $P_{\mu_{m<n}^*}$ is the probability measure given all player m with $m < n$ are adopting the optimal strategy. Therefore the best response mapping is $\mu_n^{d*} : i_n \to y^*(i_n)$. Taking μ_n^{d*} into consideration, agents will choose the optimal i_n in the first place.

$$\max_{i_n \in I(n)} \quad \mathbf{E}[P_{\mu_{m<n}^*}(y^*(i_n) = \theta | n)] \tag{2.2}$$

The solution of equation (2.2) is the optimal information choice. Thus given any position n, there is an optimal binary information choice $i_n \in I(n)$. The existence and exact form of PBNE can be illustrated inductively from the beginning of the sequence. To deal with the multiple equilibria caused by indifference, we adopt a similar indifference-breaking rule as in the previous social learning literature (Banerjee, 1992)[7].

Assumption 1. *When a player is indifferent (in terms of expected payoff) between choosing private information and social information, she always chooses private information.*

Assumption 1 states that a player chooses private information when following private or social information leads to the same expected payoff. This assumption is a minor variation of the assumption in Banerjee (1992), where a player is assumed to follow private information when being indifferent. One way to rationalise this assumption is through the lens of the trembling hand perfect equilibrium (Selten, 1975). Since the predecessors might have a trembling hand (make mistakes), one should follow her own signal instead of their predecessors if the information value of these two sources are the same.[8] Our equilibrium prediction with this assumption is effectively equivalent to the extensive-form trembling hand perfect equilibria where the tremble probabilities approach to zero. Based on this assumption, the following lemmas are proposed.

Lemma 1. In PBNE, at positions 1, 2 and 3, all players choose and follow private information.

Proof. For player 1, as social information set h_1 is empty and private signal s_1 is informative, player 1 should choose and follow private signal and expect an expected accuracy (the probability of guessing the correct state) $EA(s_1) = q$. Thus $d_1 = s_1$.

For player 2, if she follows the information she observes, she knows $EA(h_2) = EA(d_1) = EA(s_1) = q$ and also $EA(s_2) = q$. Thus she is indifferent between choosing private and social information in terms of expected payoff and according to Assumption 1, she chooses and follows private signal s_2.

For player 3, if she chooses $h_3 = \{d_1, d_2\}$, she will face two possible outcomes: either decisions of the two previous players are the same ($d_1 = d_2$) or not ($d_2 \neq d_2$). Since $h_3 = \{d_1, d_2\} = \{s_1, s_2\}$, the probability of observing these two situations

[7]Another popular indifference-breaking rule (Bikhchandani et al., 1992). They assume agents choose private and social information with probability $\frac{1}{2}$ when the expected payoffs of following the two types of information are the same. In the Appendix A, I show that the main result is consistent with either assumption.

[8]For example, player 2 under Assumption 1 should choose and follow private information.

given $d_1 = s_1$ and $d_2 = s_2$ are noted as $Pr(d_1 = d_2|d_1 = s_1, d_2 = s_2)$ and $Pr(d_1 \neq d_2|d_1 = s_1, d_2 = s_2)$, respectively.

$$Pr(d_1 = d_2|d_1 = s_1, d_2 = s_2) = Pr(s_1 = s_2) = q^2 + (1-q)^2$$

$$Pr(d_1 \neq d_2|d_1 = s_1, d_2 = s_2) = Pr(s_1 \neq s_2) = 2q(1-q)$$

The expected accuracy $EA(d_1 = d_2|d_1 = s_1, d_2 = s_2)$ when player 3 faces two same decisions and follow them is given as:

$$EA(d_1 = d_2|d_1 = s_1, d_2 = s_2) = \frac{q^2}{q^2 + (1-q)^2}$$

The expected accuracy $EA(d_1 \neq d_2|d_1 = s_1, d_2 = s_2)$ when player 3 faces two different decisions and randomly choose one is simply $\frac{1}{2}$ because two independent signals cancel each other.[9] Thus total expected accuracy of social information is the sum of these two outcomes:

$$EA(d_1, d_2) = Pr(d_1 = d_2) \cdot EA(d_1 = d_2) + Pr(d_1 \neq d_2) \cdot EA(d_1 \neq d_2)$$

$$= q^2 + q - q^2 = q$$

Therefore, it shows that for player 3, choosing and following social information h_3 will yield no higher accuracy than private signal s_3. Thus by Assumption 1, player 3 will choose and follow private signal s_3 in equilibrium. □

Lemma 2. In PBNE, all players with position $n \geq 4$ choose social information.

Proof. For the fourth player (player 4), she must choose between $h_4 = \{d_1, d_2, d_3\}$ and s_4. If she chooses to acquire the social information h_4, the rational decision rule would be to follow the median (majority) among $\{d_1,\ d_2,\ d_3\}$. We will show that the accuracy of choosing social information h_4 and follow the majority will be higher than following private signal s_4.

There are 4 different cases player 4 may face when choosing social information

[9] By Bayes' rule:

$$Pr(\theta = 0|d_1 \neq d_2) = \frac{Pr(d_1 \neq d_2|\theta = 0) \cdot Pr(\theta = 0)}{Pr(d_1 \neq d_2)}$$

$$= \frac{1}{2} = Pr(\theta = 1|d_1 \neq d_2)$$

h_4:
1. all three previous guesses are correct.
2. two out of three previous guesses are correct.
3. one out of three previous guesses are correct.
4. all three previous guesses are false.

Thus only in case 1 and 2, player 4's guess will be correct if she chooses and follows social information h_4. The expected accuracy of choosing the social information h_4 for player 4 is the probability sum of case 1 and 2. Let $Pr(1,1,1)$ represent the probability that the first three players are correct about the state of the world.[10]

$$EA(h_4) = Pr(1,1,1) + Pr(1,1,0) + Pr(1,0,1) + Pr(0,1,1)$$

$$= q^3 + q^2(1-q) + q^2(1-q) + q^2(1-q) = 2q(1-q)(2q-1)$$

$$EA(h_4) - EA(s_4) = 3q^2 - 2q^3 - q = 2q(1-q)(2q-1)$$

Given $q \in (0.5, 1)$, this difference $EA(h_4) - EA(s_4) > 0$, and thus player 4 chooses social information h_4 and d_4 is the majority of d_1, d_2 and d_3.

For the fifth player ($player_5$), she faces a choice between $h_5 = \{d_1, d_2, d_3, d_4\}$ and s_5. Given $i_4 = h_4$, s_4 is not observed. Let function $\chi(i_n)$ be the total number of private signal contained in the information set i_n,

$$\chi(h_5) = \chi(h_4) = 3$$

Therefore, $EA(h_5) = EA(h_4) > EA(s_4)$ and thus $i_5 = h_5$. By induction, the same logic applies to all subsequent players:

$$\chi(h_n) = \chi(h_4) \ \forall \ n \geq 4$$

$$i_n = h_n \ \forall \ n \geq 4$$

□

Social information is ambiguous if it contains the same number of zeros and ones (a tie), and thus the expected accuracy after observing such social information is $\frac{1}{2}$.

Lemma 3. In PBNE, ambiguous social information is never observed.

[10] By the same way, for example, $Pr(1,0,1)$ stands for the probability that the player 1 and player 3 are correct while player 2 is wrong.

Proof. Agents with an odd position may potentially observe ambiguous social information. However, in equilibrium as proved in Lemma 1 and Lemma 2, player $n = 1, 3$ chooses private information and with $n = 5, 7, ..., 2C + 1$, social information is chosen but effectively learning from the first three agents where a clear majority (unique median) exists. $\square$

With above Lemmas, Proposition 1 provides a description of the equilibrium of our model.

Proposition 1. With Assumption 1, PBNE information choices i_n^* can be characterised as:

$$i_n^* = \begin{cases} s_n, & \text{if } n \leq 3 \\ h_n, & \text{if } n \geq 4 \end{cases} \tag{2.3}$$

PBNE information interpretation $y^*(i_n)$ can be characterised as:

$$y^*(i_n) = \begin{cases} s_n, & \text{if } i_n^* = s_n \\ median\ of\ \{d_1, d_2, d_3\} & \text{if } i_n^* = h_n \end{cases} \tag{2.4}$$

Two additional properties of our equilibrium are presented in the following. I begin with asymptotic learning to study the information aggregation of this model. As in Acemoglu et al. (2011), asymptotic learning is achieved if the decisions of players in later positions in a sequence convergent to the right action as the social network becomes large.

Corollary 1. In PBNE, asymptotic learning is not achieved.

Proof. In our model, asymptotic learning is achieved if $\lim_{n\to\infty} Pr(d_n = \theta) = 1$ given $P_{\mu^*_{m<n}}$. According to the equilibrium outcome of our model in Proposition 3, asymptotic learning is never achieved in our model as $\lim_{n\to\infty} Pr(d_n = \theta) = 3q^2 - 2q^3 < 1$ given $P_{\mu^*_{m<n}}$ and $q \in (0.5, 1)$. $\square$

Corollary 2. In equilibrium, agents in the cascade do not have strict preference for acquiring private information.

Proof. Corollary 2 shows that for $n \geq 4$, who are in the informational cascade, do not have strict incentive to acquire private information after observing social information. Let $\epsilon > 0$ be the cost of acquiring private information, our following proof shows that for any positive value of ϵ, player 4 does not acquire private information in equilibrium.

In equilibrium, $d_n = s_n$ for $n \leq 3$. If the following equation holds, player 4 will acquire an additional private signal. Otherwise, she does not acquire private information.

$$Pr(d_4 = \theta | s_1, s_2, s_3, s_4) - \epsilon \geq Pr(d_4 = \theta | s_1, s_2, s_3) \tag{2.5}$$

Following the same rule in the proof of lemma 1 and 2, the expected accuracy of LHS equation can be represented as:

$$\binom{4}{4} \cdot q^4 + \binom{4}{3} \cdot q^3(1-q) + \frac{1}{2}\binom{4}{2} \cdot q^2(1-q)^2 - \epsilon \tag{2.6}$$

Simplified to get:

$$3q^2 - 2q^3 - \epsilon \tag{2.7}$$

As we have previously shown that the RHS of equation (5) equals $3q^2 - 2q^3$ Therefore, for any value of $\epsilon > 0$, equation (5) does not hold.

□

In sum, Corollary 1 shows that asymptotic learning is unattainable in equilibrium when social and private information are alternatives. This result is consistent with classical information cascade models. Corollary 2 indicates that agents in the herd do not have strict incentive to acquire private information even if it is free. Consequently, information aggregation is likely to be failed even if there exist communication channels.[11] This result contradicts the classical models where communication channels are effective to aggregation information (Bikhchandani et al., 1998). Also, our information structure and the experimental design in the next chapter that agents can only acquire one source of information is not very restrictive because agents in the cascade indeed do not have incentives to acquire private information for any positive cost.

[11] For example, a social survey is one type of communication channel as the survey can ask for individuals' private judgement (before social learning). However, these methods fail in this model because when acquiring information is costly, people do not choose to obtain private information at the first place.

2.4 Level-k Analysis and Behavioural Agents

The previous section describes the equilibrium outcome for rational agents. The model of levels of reasoning relaxes the assumption of mutually consistent beliefs, while retains the idea of strategic behaviour with optimal responses (e.g. Crawford et al., 2013; Rabin, 2013). The main idea of the level-k model is to impose a certain structure on the players' beliefs about the other players' strategies and to allow for heterogeneity among the players. Specifically, agents hold different beliefs about other players' level of thinking. I apply the same assumption as in Nagel (1995) that agents hold a degenerate population-level belief where all other players are believed to be exactly one level of reasoning below oneself. If an agent believes that all her predecessors are L0, then she would adopt L1 strategy, which is the best response to L0 predecessors. By the same logic, L2 strategy is the best response to L1 predecessors, etc. Consistent with most existing studies, L0 is assumed to be uniform random in terms of all possible strategies (Crawford et al., 2013).

Additional notations are introduced as following.
$\boldsymbol{\alpha_n} \in [0,1]$ is the probability that player n chooses private information.
$\boldsymbol{\beta_n} \in [0,1]$ is the probability that player n follows the information she observes. Specifically, following information is defined as following the median of information observed, and randomize the decision with probability $\frac{1}{2}$ when the information contains multiple medians.
$\boldsymbol{i_n^{Lk}} \in \{s_n, h_n\}$ is the information choice made by player n with Lk. $k \geq 0$ and for $k = 0$, player n does not hold any belief about other agents. When $k > 0$ player n believes all predecessors being L(k-1).
$\boldsymbol{y^{Lk}(i_n)} \in \{0,1\}$ is the interpretation rule (mapping from information observed to final decision) adopted by player n after observing i_n. $k \geq 0$ and when $k = 0$, player n does not hold any belief about other agents. When $k > 0$ player n believes all predecessors being L(k-1).
$\boldsymbol{\omega_n^{Lk}} \in [0,1]$ is the perceived expected accuracy of d_n by player n herself holding the belief that all predecessors are L(k-1) for $k \geq 1$. When $k = 0$, player n does not hold any belief about other agents, and we assume ω_n^{L0} equals the objective expected accuracy of $\frac{1}{2}$. ω_n^{Lk} can also be viewed as the *confidence level* (how sure she believes her decision is correct).
$\boldsymbol{\Omega_n^{Lk}} \in [0,1]$ is the expected accuracy of choosing and following social information for player n with predecessors being L(k-1) and player n being Lk. Specifically,

we define

$$\Omega_n^{Lk} \equiv \begin{cases} Pr\big(d_n = \theta | \omega_1^{Lk}, ..., \omega_{n-1}^{Lk}; i_n = h_n; y^{Lk}(i_n)\big), & \text{if } k \geq 1; \\ \frac{1}{2}, & \text{if } k = 0. \end{cases} \tag{2.8}$$

Intuitively, Ω_n^{Lk} is the probability of matching the correct state for player n with level Lk, believing all her predecessors are L(k-1), given social information is observed and the interpretation rule $y^{Lk}(i_n)$ is utilised.

2.4.1 L0–Naive Behaviour

Since L0 agents uniform-randomly make decisions, $\alpha = \beta = \frac{1}{2}$. The objective expected accuracy of player 1 with L0 is $\beta q + (1-\beta)(1-q) = \frac{1}{2}$. That means for the following agents, the decision of player 1 is completely uninformative. The same calculation can be extended to later sequence.

$$\begin{aligned} \omega_2^{L0} &= \alpha\beta q + \alpha(1-\beta)(1-q) + (1-\alpha)\beta\Omega_2^0 + (1-\alpha)(1-\beta)(1-\Omega_2^0) \\ &= \frac{1}{2} \end{aligned}$$

Similarly, ω_2^{L0} always equals to 1/2 regardless of the value of q. That means for the following agents, the decision of player 2 is completely uninformative as well. The same way of representation applies to ω_3^{L0},..., ω_n^{L0}.

$$\omega_n^{L0} = \alpha\beta q + \alpha(1-\beta)(1-q) + (1-\alpha)\beta\Omega_n^{L0} + (1-\alpha)(1-\beta)(1-\Omega_n^{L0}) \tag{2.9}$$

It is not difficult to show that equation (2.9) equals $\frac{1}{2}$ $\forall$ n. Intuitively, since every agent is L0, social information is completely uninformative $\Omega_n^{L0} = \frac{1}{2} \rightarrow \omega_n^{L0} = \frac{1}{2}$.

2.4.2 L1–Cursed Learning

For L1 players, they act best responsively to L0 predecessors. The intuition is straightforward: if it is believed that all previous guesses are uninformative, the best one can do is to choose and follow her own private signal. Thus the $level_1$ strategy (holding the belief that all predecessors are purely random players) is always to choose and follow the private signal regardless of their position in the sequence, i.e. $i_n^{L1} = s_n$ $\forall$ n. Consequently, $\omega_n^{L1} = q$ $\forall$ n. L1 agents are individualistic because agents do not trust predecessors' rationality. L1 behaviour is the prediction of Eyster & Rabin (2005) fully-cursed equilibrium.

2.4.3 L2–Naive Learning

For L2 players, they hold the belief that all their predecessors are L1 and thus are best responding to L1 players. Consistent with Proposition 1, L2 players with $n \leq 3$ choose private information. Also, L2 players with $n \geq 4$ choose social information since it is more informative. However, in PBNE, for any $n \geq 4$, player n will decide according to the median of the first three players only in the sequence. In contrast, L2 players believe all predecessors are revealing private information and thus learn from all predecessors equally. Formally,

$$i_n^{L2} = \begin{cases} s_n, & \text{if } n \leq 3 \\ h_n, & \text{if } n \geq 4 \end{cases} \tag{2.10}$$

$y^{L2}(i_n)$ can be characterised as:

$$y^{L2}(i_n) = \begin{cases} s_n, & \text{if } i_n^{L2} = s_n \\ median\ of\ \{d_1, d_2, ..., d_{n-1}\}, & \text{if } h_n \text{ has unique median} \\ random, & \text{if } h_n \text{ has multiple median} \end{cases} \tag{2.11}$$

As a consequence, for $n \geq 4$:

$$\omega_n^{L2} = \begin{cases} \sum_{i=\frac{n}{2}}^{n-1} \binom{n-1}{i} q^i (1-q)^{n-i-1}, & \text{if } n \text{ is even} \\ \sum_{i=\frac{n+1}{2}}^{n-1} \binom{n-1}{i} q^i (1-q)^{n-i-1} + \frac{1}{2}\binom{n-1}{\frac{n-1}{2}} q^{\frac{n-1}{2}} (1-q)^{\frac{n-1}{2}}, & \text{if } n \text{ is odd} \end{cases} \tag{2.12}$$

By the strong law of large numbers:

$$\lim_{n \to \infty} \omega_n^{L2} = 1 \tag{2.13}$$

Equation (2.13) is a result of information aggregation where asymptotic learning is achieved. In other words, L2 agent believes all her predecessors are revealing independent private information and thus trust the wisdom of the crowd. In reality, L2 agents are naive learners as they take other people's decisions at face value and fail to appreciate the potential correlations in the history. Naive learners usually are overconfident about their choices due to redundancy neglect (Eyster & Rabin, 2014). In other words, naive learners hold overconfident beliefs about their decision because they fail to realise the fact that the history may be based on very few independent decisions.

2.4.4 L3–Equilibrium Strategy

For L3 players, they believe that all predecessors are L2, so they know that all predecessors will act as described in equation (2.10) and (2.11). It is straightforward to show that $i_n^{L3} = s_n$ for $n \leq 3$ since private information choice is the best response to any predecessors for the first three players.

In addition, given $i_n^{L2} = s_n$ for $n \leq 3$, $i_4^{L3} = h_4$ as we have proved in Lemma 2. As L3 agents believe that $i_n^{L2} = h_n$ for $n \geq 3$, they know that information aggregation is very limited to only the first three players. Therefore, the interpretation rule of L3, i_n^{L3} is the same as the PBNE interpretation $y^*(i_n)$. In other words, L3 agents are learning cautiously (only based on the first three players) because they can anticipate the redundancy in the history. Since L3 strategy is indeed PBNE strategy, L4 strategy (the best response to L3) is the same as L3. By the same logic, all the higher levels of reasoning players will behave as the same as L3.

Position	**Info Choice**				**Info Interpretation**			
$\boldsymbol{n}$	***L0***	***L1***	***L2***	***L3***	***L0***	***L1***	***L2***	***L3***
1	s_1	s_1	s_1	s_1	rand	fol s_1	fol s_1	fol s_1
2	rand	s_2	s_2	s_2	rand	fol s_2	fol s_2	fol s_2
3	rand	s_3	s_3	s_3	rand	fol s_3	fol s_3	fol s_3
4	rand	s_4	h_4	h_4	rand	fol s_4	naive fol h_4	fol h_4
≥ 5	rand	s_n	h_n	h_n	rand	fol s_n	naive fol h_n	fol h_n

Note: We assume player 1 cannot choose h_1 since $h_1 = \varnothing$.
rand stands for a random choice.
fol stands for an interpretation rule that follows the median of the observed information with the appreciation of redundancy. Specifically, fol s_n means follow the private signal observed. fol h_n means follow the median of $\{d_1, d_2, d_3\}$ $\forall$ n. Whereas *naive fol* stands for an interpretation rule that follows the median of all predecessors (without appreciation of redundancy). Specifically, naive fol means follow the median of $\{d_1, d_2, ..., d_{n-1}\}$ $\forall$ n

Table 2.1: A Summary of Information Choice and Interpretation with Level k

Position	**Perceived Accuracy (ω_n^{Lk})**			
n	***L0***	***L1***	***L2***	***L3***
1	0.5	q	q	q
2	0.5	q	q	q
3	0.5	q	q	q
4	0.5	q	$-2q^3 + 3q^2 (> q)$	$-2q^3 + 3q^2 (> q)$
≥ 5	0.5	q	converge to 1	$-2q^3 + 3q^2 (> q)$

Note: The perceived accuracy is calculated given the information choice and interpretation listed in Table 2.1. It is the accuracy "perceived" by the corresponding agent. **converge to 1** refers to equation (2.13): $\lim_{n\to\infty} \omega_n^{L2} = 1$

Table 2.2: A Summary of Perceived Accuracy with Level k

2.5 Extension: Costly Information (Endogenous Acquisition)

In this section, I extend the baseline model by introducing information acquisition cost and relax the assumption that only one type of information can be observed. Assume agents now can acquire either private or social or both information for some costs. We normalise the payoff of correct decision to 1, and 0 otherwise: $\pi(d_n|d_n = \theta) \equiv 1$; $\pi(d_n|d_n \neq \theta) \equiv 0$. Most notations are consistent with our previous definition. A new information set is denoted as $\widetilde{I(n)}$ where $i_n \in \widetilde{I(n)} = \{\varnothing, s_n, h_n, \{s_n, h_n\}\}$. Agents have to choose one and only one element from $\widetilde{I(n)}$ as their information choice i_n. Let $C(i_n)$ be the cost of acquiring information. $C(s_n)$ be the cost of acquiring private information, $C(h_n)$ be the cost of acquiring social information and $C(s_n, h_n)$ be the cost of acquiring both. For simplicity, we consider the case where $C(\varnothing) = 0$ and $C(s_n) = C(h_n) = \frac{1}{2}C(s_n, h_n) = C > 0$. After observing i_n, agents make a final decision d_n. We now show that our equilibrium outcome varies with different values of C.

2.5.1 High cost

We show that when the acquisition cost is high, no information is acquired in equilibrium.

Lemma 4. Neither social nor private information is ever acquired in equilibrium if $C > q - \frac{1}{2}$.

Proof. Lemma 4 states the fact the when information acquisition cost is too high, agents will make final decisions without any private or social information. Analogously, when the benefit of information acquisition is lower than the acquisition cost, no information is acquired. Formally, $i_n = \varnothing$ if and only if:

$$\mathbf{E}[\pi(d_n|i_n = \varnothing, y'(\varnothing))] > \mathbf{E}[\pi(d_n|i'_n \neq \varnothing, y'(i_n))] - C(i_n) \ \forall\ i'_n \neq \varnothing \tag{2.14}$$

Where $y'(i_n)$[12] is the optimal mapping from information i_n to decision d_n given the probability measure of the stochastic process $\{d_n\}$ in this game, $\widetilde{P_\mu}$. Equation 2.14 is the information acquisition rule adopted by player n. The left hand side part of Equation 2.14 has a constant value given $y'(\varnothing)$ and uniform distributed θ:

$$\mathbf{E}[\pi(d_n|i_n = \varnothing, y'(\varnothing))] = \frac{1}{2} \ \forall\ n \tag{2.15}$$

Equation 2.15 shows that the expected payoff of acquiring no information is $\frac{1}{2}$. With the above equations, Lemma 4 can be proved inductively. For player 1, $h_1 = \varnothing$ so the only sensible information acquisition is $i_1 = s_1$. Her expected payoff of acquiring s_1 is:

$$\mathbf{E}[\pi(d_1|i_1 = s_1, y'(s_1))] - C(i_1) = q - C \tag{2.16}$$

Given $C > q - \frac{1}{2}$, Equation 2.16 has a value $< \frac{1}{2}$. Therefore, $i_1 = \varnothing \implies \pi(d_1) = \frac{1}{2}$ and $\chi(h_2) = 0$. Thus for player 2, she knows social information h_2 is uninformative and thus effectively face the same situation as player 1. As a consequence, $i_2 = \varnothing \implies \pi(d_2) = \frac{1}{2}$ and $\chi(h_3) = 0$. By the same logic, we can show that $\chi(h_n) = 0 \ \forall\ n$ and $i_n = \varnothing \ \forall\ n$.

□

2.5.2 Medium cost

We show that when the acquisition cost is medium, agents will behave the same as we described in our baseline model where only one type of information can be observed.

Lemma 5. Informational cascade forms and persists with probability 1 for $n \geq 4$ if $C \in (-2q^3 + 3q^2 - q,\ q - \frac{1}{2}]$.

[12] We define $y'(\varnothing)$ as a discrete unif$\{0,\ 1\}$. In other words, when player n observes no information, her final decision d_n is equally likely to be 0 or 1.

Proof. For player 1, $i_1 = s_1$ since Equation 2.16 $\geq$ Equation 2.15 when $C \leq q - \frac{1}{2}$. Consequently, $\pi(d_1) = q$ and $\chi(h_2) = 1$.
For player 2, by the same logic for player 1, $i_2 \neq \varnothing$. In addition, her preference for i_2 is $s_2 \sim h_2 \succ \{s_2, h_2\}$ as:

$$\begin{aligned}\mathbf{E}[\pi(d_2|i_2 = \{h_2, s_2\}, y'(i_2))] - C(i_2) &= q^2 + q(1-q) - 2C \\ &= q - 2C < q - C\end{aligned} \tag{2.17}$$

By Assumption 1, we conclude that $i_2 = s_2$, $\pi(d_2) = q$ and $\chi(h3) = 2$.
For player 3, by the same logic for player 1, $i_3 \neq \varnothing$. By Lemma 1, $s_3 \sim h_3$. We then calculate the expected payoff for $i_3 = \{s_3, h_3\} = \{s_1, s_2, s_3\}$ by the same process shown in the proof of Lemma 2:

$$\mathbf{E}[\pi(d_3|i_3 = \{s_3, h_3\}, y'(i_3))] - C(i_3) = -2q^3 + 3q^2 - 2C \tag{2.18}$$

Given $C \in (-2q^3 + 3q^2 - q,\ q - \frac{1}{2}]$, Equation 2.18 $< q - C$. Thus for player 3, $s_3 \sim h_3 \succ \{s_3, h_3\}$. By Assumption 1, we conclude that $i_3 = s_3$, $\pi(d_3) = q$ and $\chi(h4) = 3$.
For player 4, since $h_4 = \{d_1, d_2, d_3\} = \{s_1, s_2, s_3\}$, as described in Lemma 2, $h_4 \succ s_4$ because:

$$\mathbf{E}[\pi(d_4|i_4 = h_4, y'(i_4))] - C(i_4) = -2q^3 + 3q^2 - C > q - C \tag{2.19}$$

In addition, Corollary 2 suggests:

$$\mathbf{E}[\pi(d_4|i_4 = \{s_4, h_4\}, y'(i_4))] - C(i_4) = -2q^3 + 3q^2 - 2C \tag{2.20}$$

By comparing the payoff of Equation 2.19 and 2.20, we show that for i_4: $h_4 \succ \{s_4, h_4\}$. Therefore, $i_4 = h_4$, $\pi(d_4) = -2q^3 + 3q^2$ and $\chi(h_5) = 3$.
For $n \geq 5$, as shown in the proof of Lemma 2, $i_n = h_n$, $\pi(d_n) = -2q^3 + 3q^2$, $\chi(h_n) = 3$. Informational cascade persists.

□

2.5.3 Low cost

We show that when the acquisition cost is low, player 3 acquires both private and social information. In addition, consistent with the case of medium cost, informational cascade forms and persists for sure for $n \geq 4$.

Lemma 6. Both social and private information are acquired for $n = 3$ if $C \in (0, -2q^3 + 3q^2 - q]$.

Proof. Follow the same analysis in the proof of Lemma 5, player 1 and player 2 choose private information ($i_1 = s_1$ and $i_2 = s_2$). The expected payoff for player 3 with $i_3 = \{s_3, h_3\}$ is:

$$\mathbf{E}[\pi(d_3|i_3 = \{s_3, h_3\}, y'(i_3))] - C(i_3) = -2q^3 + 3q^2 - 2C \tag{2.21}$$

Given $C \in (0, -2q^3 + 3q^2 - q]$, Equation 2.21 $\geq q - C$(the expected payoff of $i_3 = s_3$ and $i_3 = h_3$). Therefore $i_3 = \{s_3, h_3\}$ and $d_3 = median\ of\ \{s_1, s_2, s_3\}$ $\Longrightarrow \pi(d_3) = -2q^3 + 3q^2$, $\chi(h_4) = 3$.

□

Lemma 7. Informational cascade forms and persists with probability 1 for $n \geq 4$ if $C \in (0, -2q^3 + 3q^2 - q]$.

Proof. In the proof of Lemma 6, we show that $d_1 = s_1$, $d_2 = s_2$ and $d_3 = median\ of\ \{s_1, s_2, s_3\}$. In this proof, we show that $i_4 = h_4$ and $d_4 = d_3 = median\ of\ \{s_1, s_2, s_3\}$. As $h_3 \succ s_3$, $h_4 \succ s_4$. We only need to show that $h_4 \succ \{s_4, h_4\}$ so that $i_4 = h_4$. player 4 knows that effectively $h_4 = \{s_1, s_2, d_3\}$ where $d_3 = median\ of\ \{s_1, s_2, s_3\}$.
First, we show that the expected accuracy of d_4 given $i_4 = h_4$ is the same as d_3 given $i_3 = \{s_3, h_3\}$ because $\chi(h_4) = \chi(\{s_3, h_3\}) = 3$ (they share the same information):

$$\mathbf{E}[\pi(d_4|i_4 = h_4, y'(i_4))] = \mathbf{E}[\pi(d_3|i_3 = \{s_3, h_3\}, y'(i_3))] = -2q^3 + 3q^2 \tag{2.22}$$

Second, we show that the expected accuracy of d_4 given $i_4 = \{s_4, h_4\}$ is the same as d_4 given $i_4 = h_4$. There are two possible cases of $h_4 = \{d_1, d_2, d_3\}$: Case (a) $d_1 = d_2 \iff s_1 = s_2$ and Case (b) $d_1 \neq d_2 \iff s_1 \neq s_2$. The probability of observing these two cases are denoted as $Pr(a)$ and $Pr(b)$ respectively and

$Pr(a)+Pr(b)=1$. Therefore we have $Pr(a)=q^2+(1-q)^2$ and $Pr(b)=2q(1-q)$. In Case (a), $d_3=d_1=d_2\ \forall\ s_3$ because in the case $s_3\neq s_1$ and $s_1=s_2$, following s_1 is more likely to be correct:

$$\begin{aligned} Pr(s_1=\theta|s_1=s_2\neq s_3) &= \frac{Pr(s_1=s_2\neq s_3|s_1=\theta)\cdot Pr(s_1=\theta)}{Pr(s_1=s_2\neq s_3)} \\ &= q > 1-q \end{aligned} \tag{2.23}$$

Therefore in Case (a), $d_3=d_1=d_2$. d_3 is independent of s_3 and such independence implies $d_4=d_1=d_2=d_3$ because Equation 2.24 provides exactly the same result as Equation 2.23:

$$\begin{aligned} Pr(d_1=\theta|d_1=d_2=d_3\neq s_4) &= \frac{Pr(s_1=s_2\neq s_4|s_1=\theta)\cdot Pr(s_1=\theta)}{Pr(s_1=s_2\neq s_4)} \\ &= q > 1-q \end{aligned} \tag{2.24}$$

Equation 24 indicates that player 4 with $i_4=\{s_4,h_4\}$ makes final decision $d_4=d_1$ in Case (a) regardless of s_4. Let $\Pi(a)$ be the expected payoff of player 4 with $i_4=\{s_4,h_4\}$ facing Case (a), then we have:

$$\begin{aligned} \Pi(a) &= Pr(s_1=\theta|s_1=s_2)\cdot Pr(s_4=\theta)+Pr(s_1=\theta|s_1=s_2)\cdot Pr(s_4\neq\theta) \\ &= \frac{q^2\cdot q}{q^2+(1-q)^2}+\frac{q^2\cdot(1-q)}{q^2+(1-q)^2}=\frac{q^2}{q^2+(1-q)^2} \end{aligned} \tag{2.25}$$

In Case (b), $d_3=s_3$ because in the case $s_1\neq s_2$, following s_3 is more likely to be correct:

$$\begin{aligned} Pr(s_3=\theta|d_1\neq d_2) &= \frac{Pr(d_1\neq d_2|s_3=\theta)\cdot Pr(s_3=\theta)}{Pr(d_1\neq d_2)} \\ &= q > 1-q \end{aligned} \tag{2.26}$$

Let $\Pi(b)$ be the expected payoff of player 4 with $i_4=\{s_4,h_4\}$ facing Case (b), then:

$$\begin{aligned}\Pi(b) &= Pr(s_3 = s_4, s_4 = \theta | s_1 \neq s_2) + Pr(s_3 \neq s_4, s_4 = \theta | s_1 \neq s_2) \\ &= \frac{2q(1-q)\cdot q^2}{2q(1-q)} + \frac{2q(1-q)\cdot q(1-q)}{2q(1-q)} = q\end{aligned} \tag{2.27}$$

Therefore,

$$\begin{aligned}\mathbf{E}[\pi(d_4 | i_4 = \{s_4, h_4\}, y'(i_4))] &= Pr(a)\cdot\Pi(a) + Pr(b)\cdot\Pi(b) \\ &= [q^2 + (1-q)^2]\cdot[\frac{q^2}{q^2+(1-q)^2}] + 2q(1-q)\cdot q \\ &= -2q^3 + 3q^2 \\ &= \mathbf{E}[\pi(d_4 | i_4 = h_4, y'(i_4))]\end{aligned} \tag{2.28}$$

Given $C(i_4 = \{s_4, h_4\}) > C(i_4 = h_4)$, $h_4 \succ \{s_4, h_4\}$. $\square$

Proposition 2. In the case of costly information acquisition: no private nor social information is ever acquired if acquisition cost is high; informational cascade forms and persists with probability 1 for $n \geq 4$ if acquisition cost is medium or low.

Proposition 2 is a summary of Lemma 4 to 7. Figure 2.1 provides a graphical illustration on the defined high, medium and low cost. Table 2.3 summarises the predicted information choice and interpretation with high, medium and low cost. Table 2.4 lists the expected accuracy of each position.

Apart from the case where information is too costly to acquire, Proposition 2 provides a very consistent result with our baseline model that informational cascade forms and persists deterministically. Agents in the cascade do not acquire private information even the cost is arbitrarily small. Therefore, the classical social learning models' idea that social learning is an information interpretation problem does not apply to reality where information is costly. Instead, in this paper we propose that social learning is mainly an information acquisition task.

Our model of costly acquisition can be illustrated through a simple example. The high cost scenario is similar to a decision of choosing from two restaurants for a quick lunch. The information acquisition cost, in this case, is relatively high

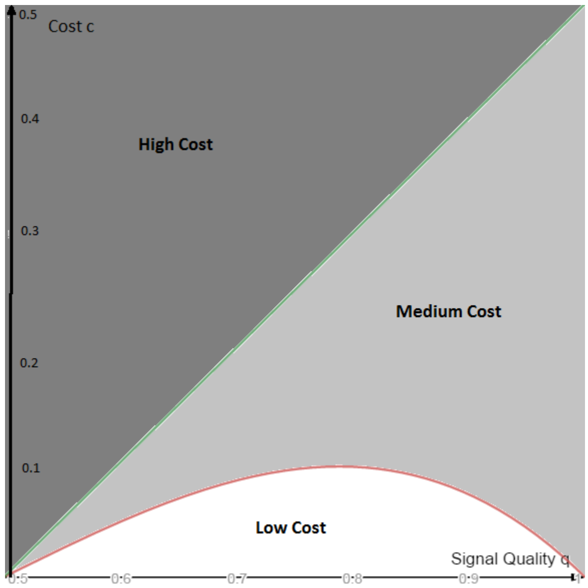

Figure 2.1: Cost of Information: High, Medium and Low

Note: The horizontal axis stands for the signal quality $q \in (0.5, 1]$. The vertical axis stands for the acquisition cost $C > 0$. Given any q, these two curves separate this box into three regions. The area above the green line represents the high cost situation. The area above the red curve and below the green line represents the medium cost situation. The area below the red curve represents the low cost situation.

because the importance of such decision is low. Therefore many people in reality simply flip a coin instead of acquiring private or social information (examine the menu, talk with waiters, watch for the decision made by others, etc). Also, the medium cost scenario is close to a decision of choosing from two restaurants for a weekend dinner. The decision is more important than the previous case but not critical. Thus people want to acquire some information either social or private depending on the circumstance but *never both* because acquisition cost is still relatively significant. Finally, the low cost scenario mimics the dining decision of an important occasion. In such case, although in the long run, people choose to observe social information only, some people opt to acquire *both* private and social information to make better decisions.

Position	Info Choice			Info Interpretation		
n	High	Medium	Low	High	Medium	Low
1	$\varnothing$	s_1	s_1	rand	fol s_1	fol s_1
2	$\varnothing$	s_2	s_2	rand	fol s_2	fol s_2
3	$\varnothing$	s_3	$\{s_3, h_3\}$	rand	fol s_3	fol $\{s_3, h_3\}$
4	$\varnothing$	h_4	h_4	rand	fol h_4	fol h_4
≥ 5	$\varnothing$	h_n	h_n	rand	fol h_n	fol h_n

Note: *fol* stands for an interpretation rule that follows the median of the observed information with the appreciation of redundancy. Specifically, fol s_n means follow the private signal observed. fol $\{s_3, h_3\}$ means follow the median of $\{d_1, d_2, s_3\}$. fol h_n means follow the median of $\{d_1, d_2, d_3\}$ $\forall$ n.

Table 2.3: A Summary of Information Choice and Interpretation with Acquisition Cost

Position	Expected Accuracy		
n	High	Medium	Low
1	1/2	q	q
2	1/2	q	q
3	1/2	q	$-2q^3 + 3q^2 (> q)$
4	1/2	$-2q^3 + 3q^2 (> q)$	$-2q^3 + 3q^2 (> q)$
≥ 5	1/2	$-2q^3 + 3q^2 (> q)$	$-2q^3 + 3q^2 (> q)$

Note: The expected accuracy is calculated given the information choice and interpretation listed in Table 2.3.

Table 2.4: A Summary of Expected Accuracy with Acquisition Cost

2.6 Conclusion

This paper presents a new theoretical model that addresses information acquisition in social learning. Classical social learning models assume that both private and social information are freely available. In contrast, in the present model players must first choose which type of information to acquire and then make a decision based on the observed information. I believe this model serves as a complement to the classical social learning model since it captures the costly information acquisition aspect of everyday decisions. Our theoretical framework provides a clear-cut prediction that starting from the fourth player in a sequence, information cascades form deterministically, rather than stochastically as in the classical models. Also, in contrast to the existing social learning models where asymptotic learning can be achieved through communication channels, we show that wisdom of the crowds never fully happen because players have no strict incentives to acquire private information even if it is free.

For behavioural agents, we show that a level-k analysis can capture interesting heterogeneity. As argued by Duffy et al. (2017), individuals can be classified into three groups regarding their attitudes towards social learning. Apart from rational individuals who learn from other when they should, “lone wolves” are used to denote the players who are biased against social learning; on the other hand, “herd animals” are those who are biased to social learning. Specifically in the present model, L1 players are individualistic lone wolves because they do not trust predecessors’ rationality. L2 players are naive learners (herd animals) who neglect the correlation and redundancy in the history. L3 players are those consistent with equilibrium predictions.

We also extend our baseline model to the environment of costly endogenous acquisition. Our analysis shows that the main result from our baseline model can capture the costly acquisition situations very well. If information is ever acquired in the sequence (acquisition cost is not too high), informational cascade forms deterministically. Also, only if acquisition cost is low enough, both private and social information are acquired simultaneously, but only once in a sequence. This result strongly challenges the classical setup where agents make decisions with access to both private and social information. We test this model experimentally in Chapter 3 of this thesis.

Appendices

A Analysis with Assumption 2

In this appendix, we revisit our key results derived in the main body with a different tie-breaking rule. In contrast to Assumption 1 that agents choose private information when being indifferent, Assumption 2 (as in Bikhchandani et al. (1992)) expects agents to behave randomly.

Assumption 2. *When a player is indifferent (in terms of expected payoff) between choosing private information and social information, she chooses private information with probability* $\frac{1}{2}$.

In the following sub-sections in this appendix, we revisit the lemmas, corollaries and propositions in the main text with Assumption 2.

Rational agents, private/social information are alternatives

Lemma 1

Lemma 1 states that with Assumption 1, no social learning appears when $n \leq 3$. With Assumption 2, clearly Lemma 1 does not hold.
For player 2, she knows $EA(h_2) = EA(d_1) = EA(s_1) = q$ and also $EA(s_2) = q$. Thus she is indifferent between choosing private and social information in terms of expected payoff and according to Assumption 2, she chooses social/private information with probability $\frac{1}{2}$.

For player 3:

$$EA(h_3) = q(\frac{1}{2}q + \frac{1}{2}) + \frac{1}{2}[q\frac{1}{2}(1-q) + (1-q)\frac{1}{2}q]$$

$$= q$$

Therefore player 3 is indifferent between private and social information and thus chooses each with probability $\frac{1}{2}$.

Lemma 2

Lemma 2 states that with Assumption 1, social learning occurs for sure for $n \geq 4$. We show that Lemma 2 holds with Assumption 2 and the proof is very similar to the proof for Lemma 2.

Proof. For the fourth player (player 4), she must choose between $h_4 = \{d_1, d_2, d_3\}$ and s_4. If she chooses to acquire the social information h_4, the rational decision rule would be to follow the median (majority) among $\{d_1$, d_2 and $d_3\}$. We will show that the accuracy of choosing social information h_4 and follow the majority will be higher than following private signal s_4.

There are 4 different cases player 4 may face when choosing social information h_4:
1. all three previous guesses are correct.
2. two out of three previous guesses are correct.
3. one out of three previous guesses are correct.
4. all three previous guesses are false.
Thus only in case 1 and 2, player 4's guess will be correct if she chooses and follows social information h_4. So we can treat the probability of occurrence of case 1 and 2 as the expected accuracy of choosing the social information h_4 for player 4.
In case 1, d_1, d_2, d_3 are all correct, thus:

$$Pr(1,1,1) = \underbrace{q}_{n=1} \cdot \underbrace{(\frac{1}{2}q + \frac{1}{2})}_{n=2} \cdot \underbrace{(\frac{1}{2}q + \frac{1}{2})}_{n=3}$$

In case 2 three situations are possible:

a. d_1 is correct, d_2 is correct, d_3 is false, thus:

$$Pr(1,1,0) = \underbrace{q}_{n=1} \cdot \underbrace{(\frac{1}{2}q + \frac{1}{2})}_{n=2} \cdot \underbrace{\frac{1}{2}(1-q)}_{n=3}$$

b. d_1 is correct, d_2 is false, d_3 is correct, thus:

$$Pr(1,0,1) = \underbrace{q}_{n=1} \cdot \underbrace{\frac{1}{2}(1-q)}_{n=2} \cdot \underbrace{(\frac{1}{2}q + \frac{1}{2} \cdot \frac{1}{2})}_{n=3}$$

c. d_1 is false, d_2 is correct, d_3 is correct, thus:

$$Pr(0,1,1) = \underbrace{(1-q)}_{n=1} \cdot \underbrace{\frac{1}{2}q}_{n=2} \cdot \underbrace{(\frac{1}{2}q + \frac{1}{2} \cdot \frac{1}{2})}_{n=3}$$

Thus the total expected accuracy of choosing and following h_4 is:

$$EA(h_4) = Pr(1,1,1) + Pr(1,1,0) + Pr(1,0,1) + Pr(0,1,1)$$

Simplified to get:

$$EA(h_4) = \frac{1}{4}q(3 + 3q - 2q^2)$$

$$EA(h_4) - EA(s_4) = \frac{1}{4}q(3 + 3q - 2q^2) - q = \frac{1}{4}q(1-q)(2q-1)$$

Given $q \in (0.5, 1)$, this difference $EA(h_4) - EA(s_4) > 0$, and thus player 4 chooses social information h_4 and $d_4 = median\ of\ \{d_1, d_2, d_3\}$. □

Although the above proof shows that consistent with the main text under Assumption 1 that social learning starts for sure at player 4, it should be noted that information aggregation is even less efficient with Assumption 2. The difference in social learning information premium between Assumption 1 and Assumption 2 is $\frac{7}{4}q(1-q)(2q-1) > 0$.

Lemma 3

With Assumption 2, ambiguous social information maybe observed for player 3 since she chooses social information with probability $\frac{1}{2}$. The probability of player 3 observing ambiguous social information (given social information is chosen) is:

$$Prob(d_1 \neq d_2) = q\frac{1}{2}(1-q) + (1-q)\frac{1}{2}q = q(1-q)$$

Proposition 3

Proposition 3. With Assumption 2, PBNE information choices i_n^* can be characterised as[13]:

$$i_n^* = \begin{cases} s_n, & \text{if } n = 1 \\ random, & \text{if } 2 \leq n \leq 3 \\ h_n, & \text{if } n \geq 4 \end{cases} \tag{29}$$

PBNE information interpretation $y^*(i_n)$ can be characterised as[14]:

[13]random stands for choosing private/social information with probability $\frac{1}{2}$.

[14]follow stands for following the information she chooses. Thus if her random choice of information is indeed s_n, she follows the private signal; and follows h_n if otherwise. When h_n is ambiguous, $d_n = 0$ with probability $\frac{1}{2}$.

$$y^*(i_n) = \begin{cases} s_n, & \text{if } i_n^* = s_n \\ follow, & \text{if } i_n^* = random \\ median\ of\ \{d_1, d_2, d_3\}, & \text{if } i_n^* = h_n \end{cases} \tag{30}$$

Corollary 1

Corollary 1 holds with Assumption 2 since $\lim_{n\to\infty} Pr(d_n = \theta) = \frac{1}{4}q(3 + 3q - 2q^2) < 1$.

Corollary 2

Corollary 2 no longer holds with Assumption 2. Instead, when agents in the cascade are uncertain about the relationship between previous actions and previous private signals, agents have a positive willingness to pay for additional private signal.

Proof. Corollary 2 shows that for $n \geq 4$, who are in the informational cascade, do not have strict incentive to acquire private information after observing social information. Let $\epsilon > 0$ be the cost of acquiring private information; the following proof shows that for any positive value of ϵ, player 4 does not acquire private information in equilibrium.

If the following equation holds, player 4 will acquire an additional private signal. Otherwise, she does not acquire private information.

$$Pr(d_4 = \theta | s_1, d_2, d_3, s_4) - \epsilon \geq Pr(d_4 = \theta | s_1, d_2, d_3) \tag{31}$$

Following the same rule in the proof of lemma 1 and 2 in this appendix, the expected accuracy of LHS equation can be represented as:

$$\begin{aligned} &Pr(1,1,1) + q[Pr(1,1,0) + Pr(1,0,1) + Pr(1,0,0) \\ &\qquad + Pr(0,0,1) + Pr(0,1,1) + Pr(0,1,0)] - \epsilon \end{aligned} \tag{32}$$

The basic idea behind the above equation is, as player 4 cannot perfectly predict whether the actions of player 2 and player 3 are results of their independent private signal, she relies on her own private signal when there exists a tie (if

$\{d_1, d_2, d_3, s_4\}$ is bimodal). Simplified to get:

$$\frac{1}{4}q(1 + 9q - 6q^2) - \epsilon \tag{33}$$

As we have shown in A that $Pr(d_4 = \theta | s_1, d_2, d_3) = \frac{1}{4}q(3 + 3q - 2q^2)$, equation 31 holds if:

$$\begin{aligned} \epsilon &\leq \frac{1}{4}q(1 + 9q - 6q^2) - \frac{1}{4}q(3 + 3q - 2q^2) \\ &\leq \frac{1}{2}q(q - 1)(2q - 1) \end{aligned} \tag{34}$$

Clearly $\frac{1}{2}q(q-1)(2q-1) > 0$ for $q \in (0.5, 1)$. Therefore, agents in the cascade have positive incentive to acquire additional private information. $\square$

CHAPTER 3 INFORMATION CHOICE IN A SEQUENTIAL SOCIAL LEARNING EXPERIMENT

3.1 Introduction

People often learn by observing the behaviour of others. The analysis of social learning in economics has grown since the two seminal papers on this topic by Bikhchandani et al. (1992) and Banerjee (1992). While many non-economists might interpret the observation of individuals following the actions of others as evidence of conformism, the insight of this theoretical literature is that apparent herd behaviour can be a rational response to the information contained in the actions of others. Still, a remaining unanswered question is precisely how much imitative behaviour can be explained by purely rational motives and how much may be due to individual bias toward social information.

Laboratory evidence on sequential social learning was first provided by Anderson & Holt (1997), and their design has become a baseline model for later researchers (see Anderson & Holt (2008) for a survey). It employs a sequential structure, where a sequence of subjects have to guess the true state of the world, observing both an informative private signal and the guesses of the subjects prior to them in the sequence. Since then, many replications and modifications to this experimental design have been studied and reported (see for example Willinger & Ziegelmeyer (1998); Hung & Plott (2001); Nöth & Weber (2003); Goeree et al. (2007)). Recently, Weizsäcker (2010) combined 13 studies containing this baseline experimental design with the help of meta-analysis to conclude that people, in general, tend to overweight their private information and thus underweight social information. In other words, people often fail to learn from others when they should, due to a bias towards using private information.

In this paper, we examine the robustness of this bias toward private information by modifying the classical social learning experiments. In their design, subjects are presented with both social information about the prior guesses of others regarding the true state of the world *and* private information about the true state of the world in the form of a noisy but informative signal. They must then guess the true state. By contrast, in our new experimental design, subjects in our experiment move sequentially (as in Anderson and Holt) but there is an additional stage to each subject's decision. In the first stage, subjects must make a choice between viewing social information (the guesses of others prior to them in the sequence) *or* receiving a noisy but informative private signal. They do *not* see both. In the second stage, after viewing the information they chose to receive, subjects must guess the true state of the world, just as in Anderson and Holt. Furthermore, each subject participates in several different sequences, making decisions in different locations in the sequence.

Our experimental design is motivated by several advantages over the classical sequential social learning design. First, by adding this additional choice stage to each subject's decision and require subjects to make such decisions multiple times in different positions, we make within-subject analysis possible. With within-subject design, individual bias for or against social information can be identified and explained by personal characteristics.[1] Second, such a design allows for more detailed and efficient identification of mistakes made by subjects. For example, we observe cases where a subject chooses to see private information but then (sub-optimally) does not follow it. In the standard social learning design, individual mistakes can only be identified when both social and private information agree and yet the subject chooses differently. Third, our design relates more closely to reality where information is usually costly. Compared with the classical setup in which both private and social information are available, our design accounts for the fact that information acquisition is usually costly, and thus before making the final decision, agents might first decide what information to acquire. Thus, arguably having to choose which information to see is more realistic than having both freely available in many real world situations. Finally, by requiring subjects to choose between social and private information (rather than giving both types of information to subjects), a potential experimenter demand effect can be eliminated. As suggested by Cooper & Rege (2011), giving subjects their own private information might suggest that it should be used or weighted more heavily. The above advantages are key motivations for our novel design.

Furthermore, we run a treatment involving a sequence of four subjects, labelled "Group", and contrast that with a treatment involving a sequence of just two subjects, labelled "Pair". This allows us to further test whether "pro-social" efficiency considerations affect the choice of private information. That is, a subject placed second in a sequence of four subjects might choose private information to improve the information content of social information for subsequent players,

[1] Classical sequential social learning experiments are all based on a between-subject design. This is because a within-subject design is impractical as the content of the social information is endogenous and thus not under the control of the experimenter.

but in a group of two, a subject should not have such motivations. While Engelmann & Strobel (2004) identify efficiency concerns in distribution experiments, efficiency in information provision has not been considered by the previous studies of social learning.

To preview our main findings, we find that most subjects choose information rationally, depending on their position in the sequence, but we also find significant and approximately equal fractions of subjects who are biased toward private or toward social information. Thus our results challenge the previous finding from information use analysis Weizsäcker (2010) that subjects overweight private information. Second, by comparing subjects' behaviour in intermediate positions and in final positions, we find that subjects tend to choose and reveal private information more when their decisions can be observed by others later in the sequence. Therefore the bias towards private information identified in previous studies might be better explained by pro-social, efficiency considerations, rather than by cognitive limitations or an experimenter demand effects. Third, subjects start choosing social information earlier in the Group treatment than is optimal, which is likely owing to their neglect of the possibility of "ties" in the private information received by earlier subjects in the sequence, thereby rendering social information useless. This tie neglect explains some of the bias we find toward social information. Fourth, we find that mistakes in information *usage* are also quite common, with approximately two thirds of subjects making guesses that are opposite to the information they chose to view at least once during the experiment. This finding further challenges the validity of classical social learning experiments where confusing actions or mistakes cannot be so clearly identified. Fifth, we find that cognitive reflection test (CRT) scores help to explain the heterogeneity in subjects' decisions rather well. In general, subjects with better reflective cognitive ability (higher CRT scores) choose optimal information more frequently and follow information more frequently. Finally, jointly with cognitive ability, we find subjects' individual traits (as identified by a post-experimental survey) and programme major can predict social learning behaviour.

Related to our experimental design, Kübler & Weizsäcker (2004) modify the Anderson and Holt design to introduce a cost for private signals. In their experiment, social information is available by default and free, however, agents have to decide whether or not to obtain a private signal at a small cost. In equilibrium, only the first player will buy the signal and all the rest imitate the first decision maker. In their experiment, however, too many private signals are bought by the subjects.

They conclude that this is due to the fact that subjects' depth of reasoning is very limited. However, in their model, errors can only be made in one direction and thus biases in favor of social information cannot be observed.

Goeree & Yariv (2015) designed an experiment aiming to disentangle information-based herding from an intrinsic taste for conformity. In their experiment, before making a decision, subjects face a choice between an informative private signal and the history actions of predecessors who have not chosen a private signal (word-of-mouth information). In equilibrium, nobody will choose this type of social information since it is uninformative. However, Goeree & Yariv (2015) find that approximately 1/3 of the information choices in their experiment are social, and conclude that for many people, herding might be a rule of thumb, rationalizing this overweighting of social information.

Importantly, private information is always strictly optimal in Goeree & Yariv (2015), and thus, there, errors can only run in one direction - towards social information. Furthermore, the long sequences employed in the existing social learning literature, including Weizsäcker (2010), leading to errors running again only in one, though opposite, direction - towards private information. In contrast, in our setup, either social or private information can be optimal depending on the situation, allowing for errors in either direction. If anything, our overall design slightly favours mistakes towards social information (when compared to equilibrium predictions).

Related to our work, De Filippis et al. (2016) modify the Anderson and Holt setup by adding a belief elicitation stage after subjects observe the decisions of others and once again after they have received their own private signal. This design enables them to assess the extent to which subjects update their beliefs, conditional on each type of information received. They report that when the private signal confirms the subjects' first belief, they weight it according to Bayes rule, but when it contradicts their first belief, they overweight it, relative to Bayesian updating. Thus, their evidence also points to an overweighting of private information, which arises from the asymmetric manner in which agents update beliefs.

Finally, Duffy et al. (2017) also study subjects' choice of social or private information in an experiment where the aim is to guess the true state of the world. However, in their design, subjects do not move sequentially as in the standard social learning experiments. Instead, subjects have to simultaneously decide whether to use social or private information, the optimality of which depends on the persistence of the state which can change from one period to the next. As in this paper, they find that most subjects choose information rationally, those there exists a sizable and approximately equal fraction of subjects who have a clear bias for social or for private information. They label those with a bias for social information "herd animals" and those with a bias for private information "lone wolves," and we adopt this same labelling to describe types in this experiment as well.

3.2 Model and Theoretical Predictions

3.2.1 Perfect Bayesian Nash Equilibrium

See Chapter 2 for details. In short, PBNE predicts that private information should be chosen in positions 2 and 3, but social information should be chosen from position 4 on-wards.

3.2.2 Logit Quantal Response Equilibrium Predictions

An alternative theoretical framework is Logit Quantal Response Equilibrium (LQRE) (McKelvey & Palfrey, 1995). LQRE has two main advantages. First, LQRE takes the widely observed "trembling hand" behaviour into consideration and the level of tremble can be calibrated from real experimental data. In addition, instead of a sharp 1 or 0 strategy prediction from PBNE, LQRE generates predictions in terms of frequencies which are usually closer to real data.

Given the binary setup of our experiment, there are four potential strategies. We write **pf** to denote choosing private information and following it, and **pn** to denote choosing private information but guessing that the state of the world is the opposite. We note that when a subject is in position 3, the guesses of the two previous subjects might differ, resulting in an ambiguous information "tie". We thus write **sf** to denote choosing social information and following the majority when in position 4, and following the subject in position 1 otherwise.[2] Finally, **sn** denotes choosing social information and guessing the opposite of **sf**.

We normalise the payoffs to correct and incorrect guesses to 1 and 0, respectively; and assume the utility function, $u(\cdot)$ for each player is linear. Player's rationality

[2]When subjects have trembling hands, a subject at position 2 is less likely to be correct compared to a subject at position 1, as position 2 allows for an additional strategy of misusing social information.

is captured by the parameter μ with $0 < \mu < \infty$: the higher μ is, the more rational $player_i$ is.

The first player in the sequence faces only two options, to follow private signal (pf) or not (pn), thus the LQRE probability of following the private signal (which is optimal) is:

$$prob(pf)_1 = \frac{e^{\mu \cdot u(pf)_1}}{e^{\mu \cdot u(pf)_1} + e^{\mu \cdot u(pn)_1}} \tag{3.1}$$

All subsequent players in the sequence face all four strategies, and thus the LQRE probability of following the private signal is:

$$prob(pf)_n = \frac{e^{\mu \cdot u(pf)_n}}{e^{\mu \cdot u(pf)_n} + e^{\mu \cdot u(pn)_n} + e^{\mu \cdot u(sf)_n} + e^{\mu \cdot u(sn)_n}}, \forall n \geq 2 \tag{3.2}$$

In general, the predictions of LQRE depend on the value of μ, the precision parameter. For players in positions 2 and 3, the qualitatively robust prediction is that they choose private information more frequently than social, as mistakes by prior players reduce the expected accuracy of social information. However, at position 4, the value of μ does matter for determining the modal strategy choice. If μ is sufficiently low, then play is noisy enough to render social information, even in position 4, to be less accurate than private. Since play frequencies in LQRE reflect relative payoffs, this induces the LQRE to place greater probability on pf than sf in position 4 if μ is below some threshold value $\hat{\mu}$. One can calculate that for $\mu < \hat{\mu} = 8.42$, the modal action is to choose private information.

3.3 Experimental Design

The experiment consists of two main parts, and subjects were informed of the content of each part only at the beginning of that part. Specifically, at the beginning of the experiment, subjects were given written instructions for the first part. After these instructions were read aloud to ensure that these instructions were common knowledge, subjects completed a comprehension quiz to verify their understanding of these experimental instructions, before moving to making decisions in the first part. After the first part was completed, the experiment was paused, and subjects were handed out the written instructions for the second part, which were also read aloud, and were also followed by a comprehension quiz, before moving to making decisions in the second part.[3].

At the beginning of each experimental session, all subjects were randomly and

[3]Instructions used in the experiment are available upon request.

anonymously divided into groupings of four subjects, which stayed fixed for the duration of the experiment. Then each subject made decisions in two formations, a 4-subject "Group" (**G**) formation, and a 2-subject "Pair" (**P**) formation (involving a further random division of the four subject grouping into two fixed pairs). Apart from the formation size, the decision-making tasks and the environment of the "Group" and the "Pair" formations are identical.

At the beginning of each round, subjects are arranged in a randomly determined sequential order within their formation (i.e. a 4-subject "group" or a 2-subject "pair"). For each formation, nature draws one of the two urns, A and B, with commonly known equal chance, and this urn will determine the state of the world for all subjects in a given formation (which we will refer as to the formation urn). Of the three balls in urn A, two are labelled a and one is labelled b. Urn B, analogously, has two labelled b and one labelled a.

Subjects are asked one by one, according to their position in the sequence, to provide their individually incentivised guess which urn is chosen by the nature as their group (pair) urn. Before making their guess, the first subject in a given sequence is revealed their independent private signal of the state, in the form of a ball drawn (with replacement) from the formation urn. Each subsequent subject in a given sequence, prior to making their guess, have to choose to observe either 1) a private signal, in the form of a ball drawn (with replacement) from the group (pair) urn; or 2) social information, in the form of the urn guesses made by all previous subjects in the sequence.

After all decisions in a round are made, the group (pair) urn is revealed. Each subject is paid a fixed payment of £5 if her urn guess coincides with the group (pair) urn in a randomly selected round, and nothing otherwise. As a feedback, subjects were revealed history of actual urns, their urn guesses, the type of information they selected, and the content of both private and social information (i.e. both information they selected to see as well as the information not selected). However, subjects do not observe neither the others' private signals nor their information selections neither during nor after the experiment.

Subjects were informed that they would experience each position in the sequence exactly 6 times, but their position in a particular round will be randomly determined. Thus, they faced 24 rounds of the "Group" formation and 12 rounds of the "Pair" formation. To control for the potential order effect, we conducted two treatments, the "Group-Pair" treatment (**GP**) and the reversed order "Pair-

Group" treatment (**PG**). Specifically, in **PG** treatment, in the first part of the experiment, subjects made decisions in the "Pair" formation, followed by making decisions in the "Group" formation of the second part. In the **GP** treatment, the order of the two parts is reversed.[4]

After these two main parts of the experiment, the experimenter invited two volunteers from the subjects to roll physical dice to randomly select two rounds from the "Group" part and one round from the "Pair" part for real payment - so that each round of the experiment had an equal, 1/12 chance of being selected for payment. In the third part, subjects were offered a fixed payment of £3 for completing the demographic information, Cognitive Reflection Test Frederick (2005), and further questions designed to identify individual differences. Finally, subjects were invited to submit open-ended comments on their decisions in the experiment.

The experiment was conducted in eight 16-subject sessions at the Behavioural Laboratory at the University of Edinburgh (BLUE), using the software z-Tree (see, Fischbacher, 2007). The participants were randomly recruited by BLUE recruitment system and most were students at the University of Edinburgh.

Table 3.1 presents a summary of the two treatments.

	GP treatment	PG treatment
No. Sessions	4	4
Ave. Duration	103min	105min
No. Subjects per Session	16	16
No. Info Choices	18+6=24	6+18=24
No. Urn Guesses	24+12=36	12+24=36
Ave. Earnings[a]	£17.30	£18.23
Total No. Subjects	64	64

[a] Includes £5 show-up fee and £3 reward for completing survey.

Table 3.1: Summary of Treatments

3.4 Experimental Results: Between Subject

In this section, we focus on our two main questions: which information was chosen and whether the chosen information was used optimally. In particular, we are interested in whether subjects systematically choose and follow private information when it is suboptimal to do so. First, note that there are no payoff-

[4] We found no systematic order effect - see Appendix A.

relevant motives to go against the chosen information, or not to *comply* with the information. Thus, an important measure of optimality of subjects' choices is *information compliance*, or the rate of optimal use of the available information.

In what follows, we will use P1 and P2 to represent subjects in positions 1 and 2, respectively, in the Pair formation and G1-G4 to represent subjects in positions 1-4, respectively, in the Group formation.

3.4.1 Overview of Information Choice and Compliance

The aggregate statistics of subjects' behaviour is presented in Table 3.2. The first two columns give the frequency with which private and social information were chosen by subjects of different positions.

First, it is clear that there is a trend towards choosing social information at later positions in the sequence. In particular, social information is most frequently chosen at position G4, with subjects choosing social information in about 83.6% of the cases. Interestingly, the majority of subjects switch to choosing social information at position 3. Finally, if we compare the information choices of G2 and G4, biases/mistakes are of the same size for either when private or social information is optimal.

Formation	Position	**Private**	**Social**	**% pf**	**% pn**	**% sf**	**% sn**
"Pair"	P1	n/a	n/a	90.8	9.2	n/a	n/a
	P2	72.4	27.6	66.3	6.1	24.4	3.3
"Group"	G1	n/a	n/a	91.8	8.2	n/a	n/a
	G2	82.8	17.2	77.1	5.7	15.5	1.8
	G3	40.9	59.1	37.6	3.3	48.7[a]	10.4[a]
	G4	16.4	83.6	14.2	2.2	77.3	6.3

[a] Out of a total of 768 observations at G3, social information chosen 454 times, and was unambiguous (i.e. $G1G2$) in 284 observations. Among the remaining 170 cases when it was "tied" (i.e. $G1 \neq G2$), 62.4% of G3 guesses coincided with G1 guesses, and thus were interpreted as **sf**; and 37.6% of G3 guesses coincided with G2 guesses, contradicting G1 guesses, thus were interpreted as **sn**.

Table 3.2: Summary of Information Choice and Compliance by Position

The remaining columns in Table 3.2 show the distribution of the four strategies (pf - choose private and follow it; pn - choose private and do not follow; sf - choose social info and follow it (i.e. follow the majority if in position 4, or follow subject in position 1 otherwise); sn - choose social info and do not follow it) adopted by our subjects at different positions. The compliance rate, or the frequency with which subjects follow their chosen information (which is equal to the sum of $\%pf$ and $\%sf$) exceeds 90% at each position, except for the complex case of position G3. Notably, there is no difference in compliance rate between private information and social information (see the details in Table A.2 in Appendix A), suggesting that the confusion/mistakes affecting information compliance might be due to some process which is independent of the source of information.

In short, the earlier documented bias towards private information (see, Weizsäcker, 2010) is not supported by our data. First, information choices roughly approximate the PBNE theoretical predictions suggesting that subjects successfully choose social information when they should. Second, the biggest deviation from the equilibrium predictions is towards social information, not private, in position 3. Third, when it comes down to compliance rates, subjects do not discriminate between private and social information.

Finding 1. *There is no systematic bias towards either private or social information in our social learning experiment.*

3.4.2 LQRE Calibrations

In general, the frequencies with which strategies are chosen in LQRE depend on the precision parameter μ. We can estimate an appropriate value for μ using behaviour in position 1, by using the empirical average compliance rate (across both formations) at position 1 of 91.3% from Table 3.2. By substituting $prob(pf)_1 = 0.913$ into equation (3.1), and solving it, we obtain $\mu = 7.05$. We then substitute the value of $\mu = 7.05$ into equation (3.2) to calculate choice probabilities for different values of n.

As Table 3.3 shows, strategy pf (choose private information and follow it) emerges as the most frequent strategy at all positions. Importantly, LQRE prediction coincides with PBNE, except at position G4. As noted in Section 3.2.2, if the precision parameter μ is below the threshold value $\hat{\mu} = 8.42$, then play in the LQRE would be so noisy that the expected return to social information at position G4 would be lower than expected return to private information. As our calibrated value of $\mu = 7.05$ is below $\hat{\mu}$, the predicted frequency of pf is greater than that of sf at position G4 - in clear contrast to the PBNE (and also to the empirical findings of Table 3.2). Yet, LQRE predictions are not sharp at position 4 - pf and sf are predicted to have similar frequencies as the expected payoffs of these two strategies are close. Finally, note that LQRE does not fit our experimental data very well. Not only if fails to predict the large majority choosing social information at position 4 and following, it also does not predict the high frequency

Position	**PBNE**	**LQRE** ($\mu = 7.05$)	***Empirically Optimal***
G1/P1	private (pf)	$prob(pf) = 0.913$	private (pf)
G2/P2	private (pf)	$prob(pf) = 0.493 > prob(sf) = 0.402$	private (pf)
G3	private (pf)	$prob(pf) = 0.493 > prob(sf) = 0.402$	private (pf)
G4	social (sf)	$prob(pf) = 0.471 > prob(sf) = 0.435$	social (sf)

Table 3.3: Theoretical Predictions

of choice of social information in position G3. To be fair, this later "tie neglect" effect is also not picked up by PBNE, as both PBNE and LQRE predict identical strategic behaviour at G2 and G3.

3.4.3 Empirically Optimal Strategy

Weizsäcker (2010) suggests that one should also consider the empirically optimal strategies that reflect the true behaviour (rationality) of other players. That is, we should expect a rational subject to optimize with respect to the actual behaviour of his opponents rather than some idealized equilibrium. The empirically optimal action for our experiment is presented in the last column of Table 3.3. This result is calculated using the empirical data of Table 3.2. The presence of non-compliance is enough to make private information optimal at positions 2 and 3, but still compliance is high enough so that social information is still optimal at position 4. Thus, the empirically optimal strategy is the same as PBNE.

3.5 Experimental Results: Within Subject

Our within-subject design allows to compare individual subject behaviour at different positions in the sequence. We thus are interested in whether individual subject behaviour is consistent with the theoretical predictions of Table 3.3. We also are interested in documenting possible deviations from payoff-maximizing behaviour. The empirically optimal choice involves choosing social information in position G4, and following the majority of guesses, and thus a choice of private information in G4 would indicate a bias towards private information. One can observe further biases for a particular type of information by comparing subjects' choices in position G3 to choices in positions P2 and G2. Furthermore, if subjects have any additional efficiency or other-regarding preferences, one should observe further differences in behaviour in positions P2 and G2, as P2 is a final position in the sequence, while G2 is followed by two more subjects.

3.5.1 Efficiency Concerns: Information Choices at G2 vs. P2

As Banerjee (1992) pointed out, following others in a sequential learning setup can generate a negative herding externality, reducing social welfare. Hung & Plott (2001) find that when standards payoffs are replaced by majority rule, cascades form significantly less. Thus, it is plausible that subjects can identify such a herding externality on followers, and may be able to avoid herding for payoff or efficiency purposes. Furthermore, Engelmann & Strobel (2004) document, albeit in a different context, that some subjects may have efficiency concerns, desiring to maximise the sum of participants' payoffs.

We thus hypothesise that subjects with efficiency concerns may choose and reveal private information more frequently when their decision may affect the welfare of others. Specifically, we note that a subject in position 2 is a "terminal" player in the "Pair" formation, but is followed by two more subjects in the "Group" formation. Thus, if efficiency concerns exist, and subjects are able to identify the negative externality of choosing social information, they would choose private information more frequently in the position G2 than in the position P2. Indeed, by revealing private information at position G2, one can potentially improve the success rate of the follower at position G4 by 10.3% (see Chapter 2).

We find that when placed at position 2 in a sequence, the same subjects choose private information significantly more frequently at position G2 in "Group" formation than at position P2 in "Pair" formation (82.81% vs. 72.39%, Wilcoxon signed-rank test $p < 0.01$). This can be further observed in Figure 3.1 which depicts the number of private information choices by each subject in positions P2 and G2. In the absence of efficiency concerns, observations would be located symmetrically around the 45° line. The observations located above the 45° line indicate potential efficiency concerns, as these subjects choose private information more frequently at G2 than P2.

Finding 2. *Subjects choose private information more frequently when they are followed by others in the sequence, indicating a possibility of efficiency concerns.*

3.5.2 Tie Neglect: Information Choices at G3

Perhaps, the most surprising theoretical prediction of PBNE in Section 3.2.1 is that the optimal strategy at position G3 is to select private information and follow it. This result runs counter to the intuition that two equally precise independent pieces of information are more informative than only one piece of the

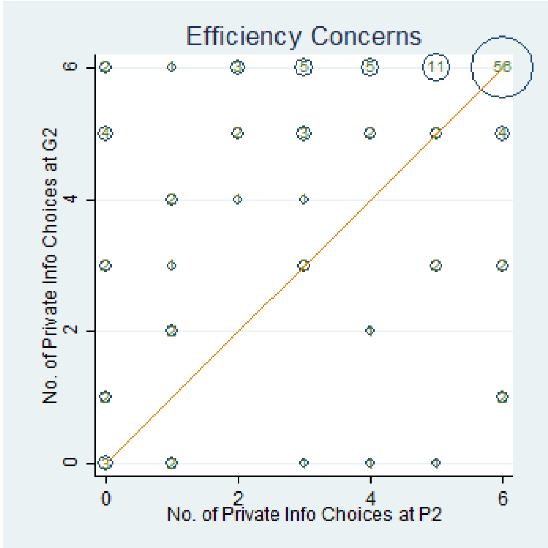

Figure 3.1: Efficiency Concerns: Private Information Choices at G2 vs. P2

Number of private information choices at G2 (y-axis) and P2 (x-axis), for each of 128 subjects. The size of the bubbles is proportional to the number of subjects with a given (x, y) value. This frequency is also stated within the bubble. The bubbles located above the 45° line indicate potential efficiency concerns.

same precision. Indeed, as in PBNE each player follows their information, social information at position G3 in the form of guesses at G1 and G2 is more accurate - but only when these guesses coincide. However, when they contradict (or "tie"), social information at G3 is noninformative. And, the expected frequency of the tie is sufficiently high to offset the informational advantages of coincident guesses. Such *tie neglect*, which is ignoring or underestimating the possibility of observing uninformative social information due to a "tie" can only happen in odd positions like G3, G5, and so on, where social information consists of even number of previous actions.

Indeed, a substantial number of subjects exhibit tie-neglect behaviour as they choose social information more frequently at position G3 than at positions G2 or P2. As Figure 3.3 demonstrates, the frequency of private information choice at G3 is significantly lower than that at positions P2 and G2 (Wilcoxon signed-rank test $p < 0.01$ for both comparisons). Specifically, in Figure 3.3 (left panel), more observations are located below 45° line, suggesting more subjects choosing private information less frequently (and thus choose social information more frequently) at position G3 compared to their terminal position P2 in the "Pair" formation. As Figure 3.3 (right panel) demonstrates, the tie neglect is even more pronounced when efficiency concerns are potentially at play, as even more subjects chose

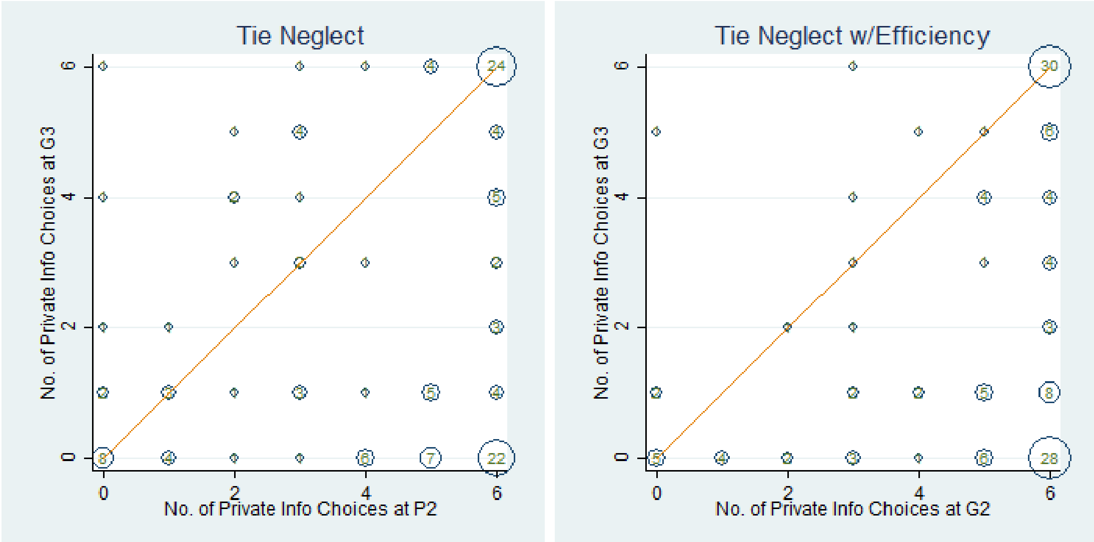

Figure 3.2: Tie Neglect: Private Information Choices at G3 vs. P2 (G2)

Number of private information choices at G3 (y-axis) versus at P2 (x-axis in the left panel) and G2 (x-axis in the right panel), for each of 128 subjects. The size of the bubbles is proportional to the number of subjects with a given (x, y) value. This frequency is also stated within the bubble. The bubbles located above the 45° line indicate potential "tie neglect".

social information more frequently at position G3 than when they were followed by the others in position G2 in the "Group" formation. That is, despite efficiency concerns potentially being at play both in positions G2 and G3, the tie neglect effect appears to be stronger than the efficiency-concerns effect.

We are not aware of any previous literature explicitly discussing and/or documenting this phenomenon.[5] The tie neglect identified here is different from the redundancy neglect documented by Eyster & Rabin (2014). Redundancy neglecting subjects sub-optimally overweight social information because they fail to recognize the correlation inherent in prior actions. While this correlation is also potentially relevant in our setup, tie neglect arises from ignoring a possibility of uninformative "anti-correlated" signals. Without tie neglect, both PBNE and LQRE predict that the frequency of private information choice at G2 and G3 should be equal regardless of the level of redundancy neglect.

Finding 3. *Subjects choose social information more frequently at position G3 than at positions G2 and P2, indicating a possibility of "tie neglect".*

[5] The indirectly relevant literature includes bounded rationality (Simon, 1982; Kahneman, 2003), subjective probability (Kahneman & Tversky, 1972), unawareness (Dekel et al., 1998; Modica & Rustichini, 1999; Heifetz et al., 2006) and two-heads-better-than-one (Cooper & Kagel, 2005).

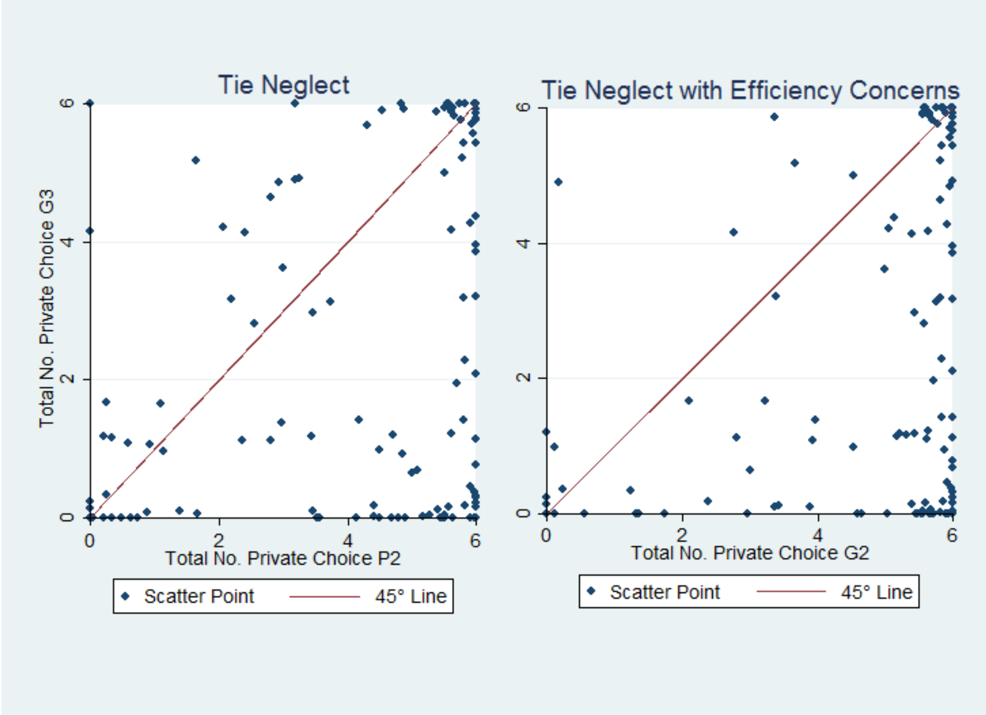

Figure 3.3: Tie Neglect: Private Information Choices at G3 vs. P2/G2

Each dot represents each of the 128 subjects' choices of private information at G3 (y-axis) versus at P2 (x-axis in the left panel) and G2 (x-axis in the right panel).

3.5.3 Optimality: Information Choices at G4 vs. P2 and G2

We are now ready to explore the degree of optimality of subjects' choice of information. Both PBNE and LQRE predict that the frequency of private information choice at G4 should be lower than at P2, G2, and G3. As we discussed earlier, subjects might be liable to social information bias at position G3 due to "tie neglect", and to private information bias at position G2 due to efficiency concerns. Thus, a pair of numbers representing each subject's choices of private information at the terminal positions G4 and P2 provides a reasonable insights into subjects' abilities to select information optimally.

Figure 3.4 (left panel) plots the information choice at G4 versus P2, and suggests an interesting pattern of choices. Note that there is a big cluster of subjects at the bottom right corner around the coordinate (6,0). These subjects behave according to the refined PBNE, and choose always private information at P2 and social information at G4. There are also two smaller clusters which are more difficult to explain using existing theories. The cluster at the bottom left corner, around the coordinate (0,0), represents subjects who always choose social information, and whose behaviour is consistent with both theories at position G4 but not at

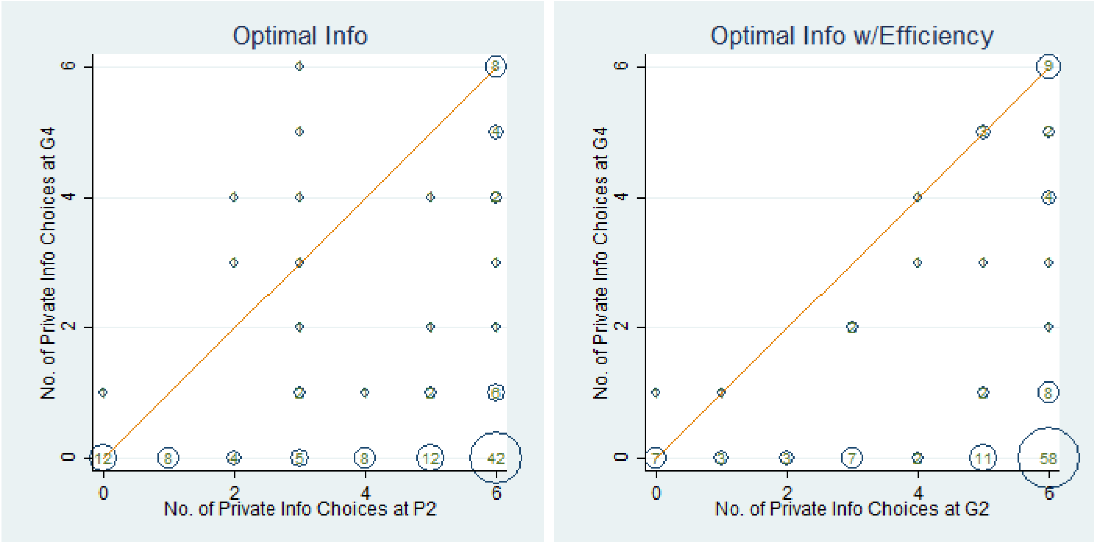

Figure 3.4: Optimality: Private Information Choices at G4 vs. P2 and G2

Number of private information choices at G4 (y-axis) versus at P2 (x-axis in the left panel) and G2 (x-axis in the right panel), for each of 128 subjects. The size of the bubbles is proportional to the number of subjects with a given (x, y) value. This frequency is also stated within the bubble. The bubbles located above the 45° line indicate tendency for optimal information choice.

position P2. The cluster at the top right corner, around the coordinate (6,6), represents subjects who always choose private information, and whose behaviour is consistent with both theories at position P2 but not at position G4. These two extreme clusters of "herd animals" (those who always choose social information) and "lone wolves" (those who always choose private information) were also found earlier in Duffy et al. (2017). Furthermore, while the combination of private information choices at positions G4 and G2 is a noisier indicator of subject's optimality because of potential efficiency concerns, nevertheless Figure 3.4 (right panel) presents the very similar result.

Finding 4. *A majority of subjects behave according to the refined PBNE, but there are also some "herd animals" and "lone wolves".*

3.5.4 Lone Wolf Index (LWI)

As we reported earlier in Finding 1, aggregate data from our experiment does not indicate any systematic bias. However, as Finding 4 states, there is substantial heterogeneity in subjects' tendencies to choose information optimally. While a majority of subjects appear to be able to optimally select information, there are also substantial number of subjects who select information optimally in some positions, but not in others.

To separate subjects' biases from their optimal decisions, we follow Duffy et al. (2017) and calculate a Lone Wolf Index (LWI) for each subject. This is defined as the total number of private information choices at the positions P2 and G4, less 6, so that LWI ranges from -6 to 6. If a subject always chooses information optimally, she selects private information 6 times at P2 and 0 times at G4, so that her LWI equals to 0, and thus she is unbiased. In contrast, if she always chooses private information, her LWI would be 6, a biased lone wolf. Analogously, her LWI would be -6 if she always chooses social information (and never private information), a biased herd animal.

The distribution of LWI is presented in the left panel of Figure 3.5. The median and modal subject is unbiased with LWI of zero, and thus either chooses the information optimally, or makes equal number of suboptimal decisions in both positions. The mean of LWI is -0.67, which is significantly different from 0 (two-tailed t-test, $p = 0.016$), suggesting that our subjects are slightly biased towards social information. A test for skewness and kurtosis gives Pr(Skewness) = 0.329 and Pr(Kurtosis) = 0.784, with adjusted $\chi^2(2) = 1.04$ ($p = 0.594$), suggesting symmetry around the mean.

We also consider a version of the Lone Wolf Index which taking into account efficiency concerns, by calculating the total number of private information choices at the positions G2 and G4, less 6. As one can see in the right panel of Figure 3.5, the distribution of this version of LWI is effectively unbiased, with a mean of -0.05 that is not significantly different from zero (two-tailed t-test, $p = 0.856$), and appears to be symmetric around the median and mode of zero. A test for skewness and kurtosis gives Pr(Skewness) = 0.544 and Pr(Kurtosis) = 0.198, with adjusted $\chi^2(2) = 2.07$ ($p = 0.356$). This suggests that, among our subjects, efficiency concerns offset the above-mentioned slight bias towards social information.

Finding 5. *A substantial number of subjects chose information optimally. Overall there is a slight bias towards choosing social information, which is offset by efficiency concerns.*

3.5.5 Total Private Information Index (TPI)

We further explore subject heterogeneity in information choice by considering *all* situations where subjects were confronted with information selection task. There were total of 24 such situations: 6 situations in "Pair" formation when subjects were in position P2, and 18 situations in "Group" formation when subjects were in positions G2-G4). Note that subjects' choices at position G3 appear to be

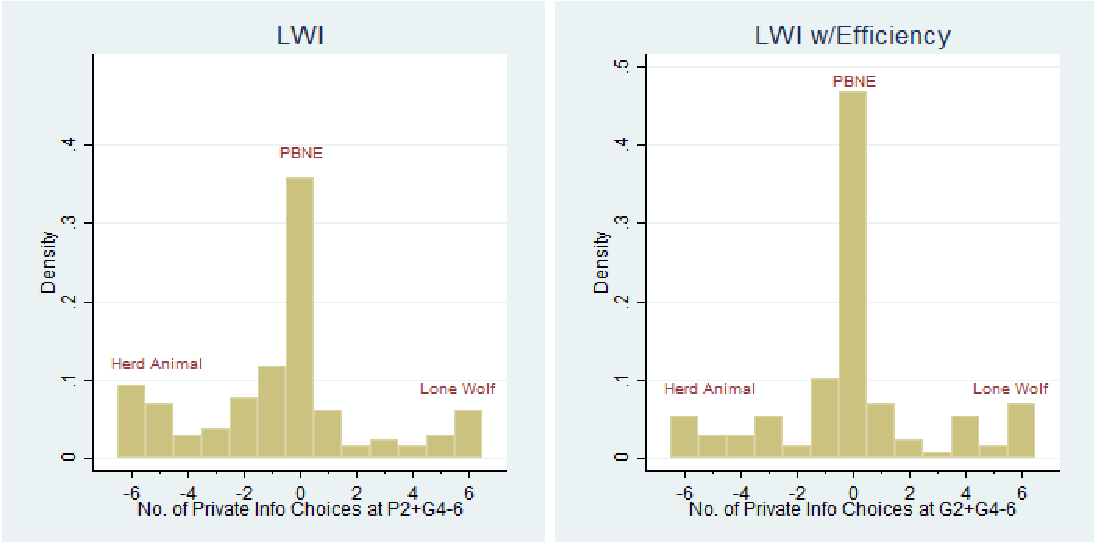

Figure 3.5: Lone Wolf Index

Distributions of the Lone Wolf Index (LWI), a measure of bias towards private information, which is a sum of subject's private information choices at G4 and P2 (G2) minus 6. It ranges from -6 to 6, with negative (positive) values indicating a bias towards social (private) information. (N of subjects = 128.) Left panel: LWI is a number of subject's private information choices at G4 and P2 (i.e. terminal positions), minus 6. Right panel: a version of LWI calculated as a number of subject's private information choices at G4 and G2 (i.e. potentially affected by efficiency concerns), minus 6.

affected by a particular failure of cognition, the "tie neglect" effect. We thus will treat the choices in that position with caution, and, to disentangle the effect of tie neglect, will also look at subjects' behaviour excluding their choices at G3.

We first generate a Total Private Information index (TPI), which is the number of all situations where a given subject selected private information out of 24 situations. Thus, TPI ranges from 0 to 24, with 0 representing subjects who never choose private information during the entire experiment, and 24 representing subjects who always choose private information. We also consider the total number of private information choices without a possibility of tie neglect, by considering all information choice situations except those at position G3 - so that in this case the range is 0 to 18. Figure 3.6 depicts the distribution of TPI including and excluding position G3 (left and right panels, respectively).

Concentrating on the left panel of Figure 3.6, it appears that no single behavioural model can explain the distribution of TPI, as it is widely spread with multiple spikes. At the left corner, there are a small group of subjects, who never or almost never choose private information (herd animals). At the opposite corner, there are a few subjects who almost always choose private information regardless of their

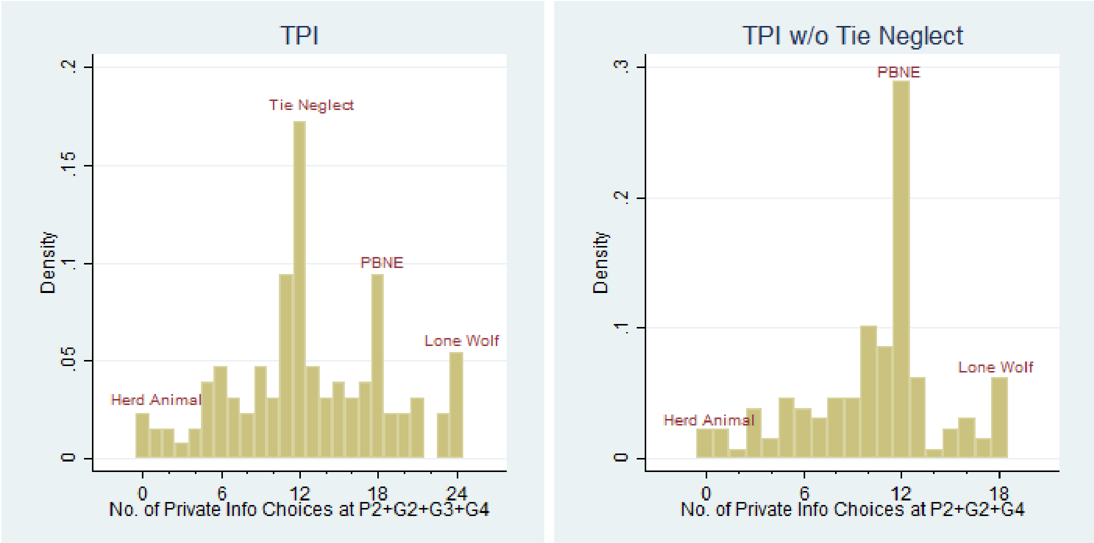

Figure 3.6: Distributions of Total No. of Private Information Choices (TPI) With and Without Tie Neglect

The Total Private Information index (TPI) is the number of situations were a given subject selected private information. Subjects who always choose private (social) information are located on the right- (left-) hand side of the range. Left panel: TPI is based on information choices at all positions (P2, G2, G3, and G4), and ranges from 0 to 24. Right panel: TPI calculated without tie neglect, for information choices only at positions P2, G2, and G4, and ranges from 0 to 18.

position (lone wolves). There are also clear spikes at 12 and 18. At 12, most are subjects choosing private information at position 2 in both "Pair" and "Group" formations, and switching to social information at position G4 (optimal) as well as at position G3 (tie neglect). At 18, most are subjects who switch to social information only at position G4, corresponding to PBNE and empirically optimal strategies. The presence of observations with other values of the TPI index indicate that many subjects are not "pure" in terms of their information choices, some of them are either updating their strategies during the experiment, or do not have stable strategies. Overall, the mean TPI of 12.75 is marginally greater than median and modal value of 12 (one-tailed t-test, $p = 0.077$), suggesting a strong presence of tie neglect, and a substantial presence of optimality.

The left panel of Figure 3.6 excludes the confusing position G3, and shows that, once one excludes the possibility of tie neglect, the modal response is optimal, with each subject choosing private information 12 times (mostly at positions P2 and G2). The distribution of total number of private information choices excluding G3 is strongly skewed towards social information with skewness of -.467 ($p = 0.03$), with mean of 10.30, and median at 11. Given our experimental design involving short sequences, one would expect such negative skewness, - which is the exact opposite of the what one would expect in an experimental design with longer sequences, such as the standard social learning experiments.

Finding 6. *There is substantial individual heterogeneity in information choice. A large group of subjects exhibited tie neglect. Once a possibility of tie neglect is excluded, optimality emerges as the most prominent behaviour, with some "lone wolves" and "herd animals".*

3.5.6 Information Optimality vs. Bias

Similarly to the above mentioned Total Private Information index (TPI), one can construct a Total Optimal Information index (TOI) by adding the number of times a particular subject chooses private information in positions P2, G2, and G3, with the number of times she chooses social information in position G4. Theoretically, TOI ranges from 0 to 24 (with 0 representing a theoretical agent who chooses the opposite of optimal information in all 24 choice situations), but its empirical range is from 6 to 24, with mean of 16.78 and standard deviation of 4.44. However, on its own, such optimality index is less interesting than its combination with a measure of bias.

In order to consider each subject's information optimality jointly with her information bias, we first, for each subject, convert the Total Optimal Information index (TOI) into the proportion of all information choices which were optimal (as a measure of total rationality), as well as convert the Total Private Information index (TPI) into the proportion of all information choices which were private (as a measure of total bias). Figure 3.7 represents the joint distribution of these two numbers.[6]

Figure 3.7 provides a graphical representation of many features of our experiment, as well as some of the above-mentioned findings. First, the dashed lines represent the constraints on the measures of behaviour. The asymmetric shape of the quad reflects that, by construction, our experimental design favours errors towards social information (as it involves short sequences). This is in contrast to the standard social learning experiments where errors tend to run towards private information (as in Weizsäcker (2010)). Second, the largest group of subjects exhibits "tie neglect", which is a novel type of bias towards social information. Third, a substantial group of subjects always made optimal information choices.

[6]Here, "Quad of Rationality" is a sequential-move counterpart of "Diamond of Rationality" of Duffy et al. (2017).

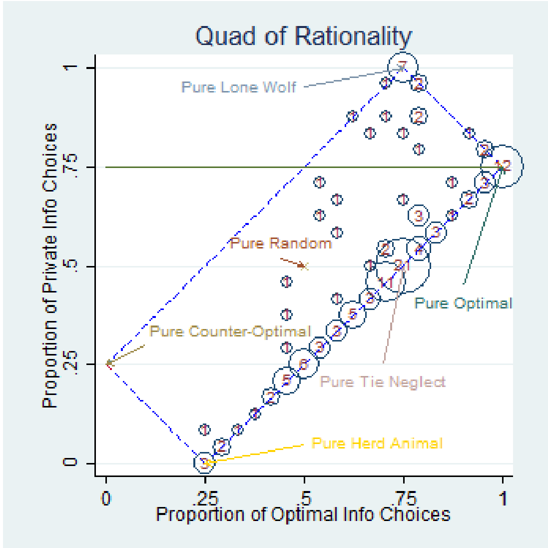

Figure 3.7: Quad of Rationality: Information Optimality vs. Bias

Proportion of private information choices out of all 24 information choices (y-axis) vs. proportion of optimal information choices out of all 24 information choices (x-axis), for each of 128 subjects. The size of the bubbles is proportional to the number of subjects with a given pair of numbers. By construction, the two values are constrained by the dashed lines.

Finally, there are some clusters of biased subjects - a noticeable cluster of "lone wolves" and a smaller cluster of "herd animals".

Finding 7. *There is substantial individual heterogeneity in optimality and bias of information choices, with "tie neglect" bias emerging as the most frequent behavioural feature, followed by optimal choice.*

3.5.7 Information Compliance Index (ICI)

Finally, we investigate potential heterogeneity in the use of information, by constructing the Information Compliance Index (ICI), which is simply the number of times a given subject followed observed information when making the payoff-relevant state guess at *all positions* (i.e. P1, P2, G1, G2, G3, and G4). As was discussed earlier, it is difficult to interpret subject's usage of information at position G3 when the guesses of the preceding players "tie". We thus used a conservative measure of information compliance, with all guesses at position G3 described as compliant, unless the previous guesses coincided (so that the social information at the position G3 revealed unambiguous majority guess), but the subject nevertheless guessed the opposite of the prior majority guess. Any value of ICI which is different from 36 represent a tendency of going against own signal or the majority. Therefore ICI ranges from 0 to 36, where 0 corresponds to sub-

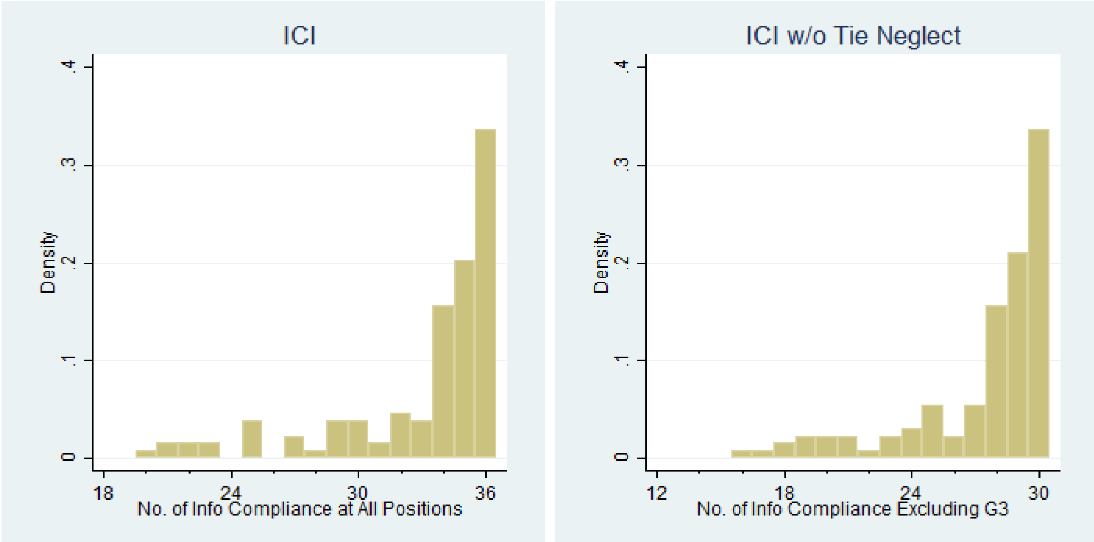

Figure 3.8: Distributions of Information Compliance Index (ICI) With and Without Tie Neglect

The Information Compliance Index (ICI) is a number of times when a subject followed observed information. (N of subjects = 128.) Left panel: ICI is based on state guesses at all positions (P1, P2, G1, G2, G3, and G4), with theoretical range from 0 to 36. Right panel: ICI calculated without tie neglect, for state guesses for all positions excluding G3, with a theoretical range from 0 to 30.

jects who never follow the selected information, or guessing the opposite of the observed information, and 36 corresponds to subjects who always comply with their observed information.

As one could see from the distribution of the ICI in Figure 3.8 (right panel), the majority of subjects are perfectly or almost perfectly rational in terms of information compliance, while at the same time approximately 67% of the subjects discard information at least once and about 34% of subjects go against information at least three times across the experiment. One could observe similar pattern of behaviour in Figure 3.8 (left panel) without a possibility of tie neglect (i.e. when position G3 is excluded).

Although in most cases information was optimally used, errors are also present, a possibility not considered by previous studies. For example, consider the standard sequential design with a binary state of the world when both private and social information is available, and suppose one observes that subject's choice coincides with the social (private) information, rather than with the private (social) one. Such behaviour would typically be interpreted as subject weighting social (private) information more than private (social) one. However, our findings suggest that this may not necessarily be always the case, as subjects may instead ignore social (private) information altogether, and go against their private (social) information.

Finding 8. *A large majority of subjects used the available information (i.e. complied with it). However, a substantial number of subjects used it sub-optimally, either going against their private signal and/or social information.*

3.6 Individual Characteristics and Information Bias

In the previous section, we have identified the existence of individual heterogeneity, not only for information choices but also for information usage. Now, we will attempt to explain such heterogeneity with personal characteristics.

In the third part of the experiment, we collected information on subjects' cognitive abilities, programme of study and potentially relevant individual traits. In this section, we attempt to link these personal characteristics to subjects' heterogeneity in information choices and information use.

3.6.1 Individual Characteristics

The average age was 22.9 years. We also collected subjects' programmes of study, as the existing literature suggested that programme of study may affect subjects' decision making - for example, economics students are found to behave differently in many experiments (e.g. Selten and Ockenfels, (1998); Frank et al. (1993)). Table 3.4 summarises the programmes of study of our subjects.

Degree	**Frequency**	**Percentage**
Non Student	5	3.91
Science/Engineering	27	21.09
Business	15	11.72
Economics	19	14.84
Arts and Social Science	62	48.44
Total	128	100

Table 3.4: Summary of Programmes of Study

Cognitive Reflection Test (CRT)

It is plausible that subjects with higher cognitive abilities perform better in our experiment, for example, they may choose optimal information and/or follow the observed information more frequently. As a proxy for subject's cognitive abilities, we use subjects' scores on the multiple-choice version of the Cognitive Reflection

Test (CRT) (Frederick, 2005). This test involves three simple questions resulting on a score ranging from 0 (all three answers are wrong) to 3 (all three answers are correct). For each question, subjects were asked to choose the answer from four choices. In our sample of subjects, the average CRT score is 1.29, and, consistent with previous evidence, we find that males have higher average scores (1.74 for males vs 1.06 for females).[7]

We define Total Optimality Index (TOI) as the number of subject's optimal information choices. It ranges from 0 to 24, where 0 corresponds to a subject who never chose information optimally (i.e. always chose opposite of PBNE prediction) and 24 corresponds to a subject whose information choices are always consistent with PBNE predictions. Figures 3.9 and 3.10 indicate that, indeed, subjects with high CRT score choose optimal information more frequently and follow information more frequently. This observation will be confirmed later by our regression analysis.

Finding 9. *Subjects with high measure of a proxy for cognitive ability choose optimal information more frequently and follow information more frequently.*

Individual Traits

It is plausible that individual personalities affect subjects' behaviour in our experiment, - for example, by biasing subjects towards a particular type of information, or affect their attitudes towards the observed information. We conducted an individual traits survey with 30 six-point scale questions, derived from Costa & McCrae (1992), Duffy & Kornienko (2010), as well as our own design. These questions constitute six motives which we label as "Contradictory," "Social Regret," "Theory of Mind," "Rivalry," "Altruism," and "Trust", using both positively and negatively keyed questions (see Appendix C).

Our first step is to assess the internal consistency (reliability) of each set of questions which are supposed to capture a particular motive. We apply a standard reliability test statistic, Cronbach's α, with higher values indicating greater intercorrelation and reliability. After discarding internally inconsistent items, four

[7] A CRT score of 1.29 out of 3 is considered as an average performance. In a recent meta-study, Brañas-Garza et al. (2015) collect data from more than 40,000 subjects across over 100 studies and find that the average CRT score is approximately 1.2 out of 3 and male subjects have higher scores than female subjects. As argued by Frederick (2005) that subjects from elite universities on average perform better, one potential reason that our sample has a lower than expected CRT performance might because we collect their CRT response after the main tasks at the end of the experiment. Brañas-Garza et al. (2012) argue that subjects completed the CRT as their last task may explain why in their sample 67% subjects scored 0 out of 3.

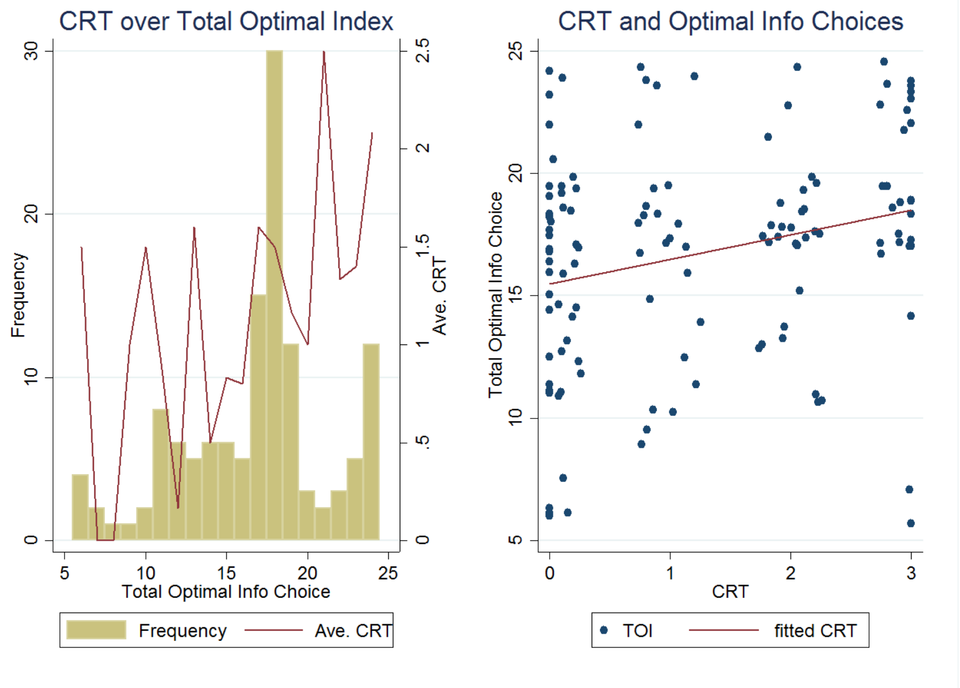

Figure 3.9: Cognitive Ability and Optimal Information Choice

Left panel: distribution of Total Optimality Index (TOI) versus average CRT score for subjects with a particular value of TOI. TOI is the number of subject's optimal information choices. Right panel: The distribution of TOI for each CRT score (jittered), together with a fitted line.

motives - "Contradictory," "Social Regret," "Theory of Mind" and "Rivalry" - have α greater than the standard cut-off value of 0.7. In addition, "Altruism" and "Trust" were marginal, with α of 0.69 and 0.68, respectively. "Trust" was excluded due to the absence of effect.

We conduct common factor analysis on the retained 21 items, which render acceptable factorability with $\alpha = 0.705$ and Kaiser-Meyer-Olkin (KMO) measure of 0.74. Factor analysis on these 21 questions generate four factors with eigenvalues greater than unity. Based on the signs and magnitudes of these factors in Table 3A.12 in Appendix C, Factor F1 can be interpreted as a tendency for being contradictory and independent; Factor F2 can be interpreted as a tendency for being social and rivalrous; Factor F3 can be interpreted as a tendency of understanding others; Factor F4 can be interpreted as a tendency of being non-altruistic.

By constructions, factors are uncorrelated. We also found that there is no significant correlation between CRT and any of the four factors. We found gender differences in the predicted values of factors for each subject (see Table 3.5). Consistently with the previous studies (e.g. Weisberg et al., 2011), females are less

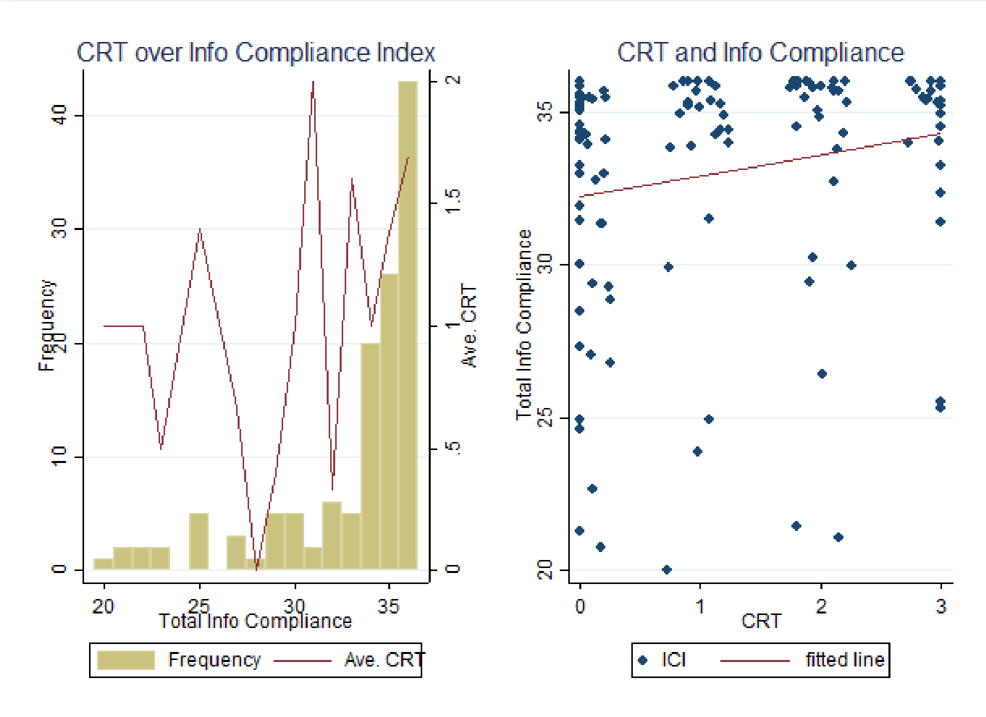

Figure 3.10: Cognitive Ability and Information Compliance

Left panel: Average CRT score for each value of ICI. Right: the distribution of ICI for each CRT score (jittered) and a fitted line.

contradictory (more dependent), less socially rivalrous than males, understand others better, and are more altruistic than males.

3.6.2 Regression Analysis

In this part, we explore whether the above-mentioned individual characteristics can explain subjects' behaviour in the lab. Robustness checks can be found in Appendix D.

Individual Characteristics and Information Choice

In this subsection, we investigate the relationship between information choices and individual characteristics. We first conduct OLS regression with dependent variable being the total number of optimal information (TOI) chosen. The independent variables are age, gender, cognitive ability (CRT), programme of study and individual traits. Details are provided in Table 3.6. Our regression results suggest that CRT scores have a significant positive effect on choosing the optimal information, consistent with the intuition that subjects with a higher cognitive ability might identify optimal strategies more frequently. In addition, business

Factors	Motives	Female
Factor 1	Contradictory	-0.2824
Factor 2	Social-rivalry	-0.3357***
Factor 3	Understanding Others	0.2315
-Factor 4	Altruistic	0.2888**

Table 3.5: Table of Individual Motives

Wilcoxon rank-sum test $p < 0.1$, *; $p < 0.05$, **; $p < 0.01$, ***.

students perform significantly worse in terms of information choices than non-student subjects and given the positive coefficients for Economics and Technical programmes, business students perform significantly worse than these two groups as well. Finally, the "Theory of Mind" factor (Factor3) is negatively correlated with choosing the optimal information. In other words, subjects who claim to be better understanding others choose optimal information less frequently.

We also explore the potential learning/experience effect by conducting a logistic regression with the dependent variable of Doptinfo, which is a dummy variable equals to 1 when the optimal information is chosen. "Time" represents the number of rounds (ranging from 1 to 36), and "Experience" represents the number of times a subject experienced a specific position in the formation (ranging from 1 to 6). We find that the logit regression results are consistent with the OLS results, and there is no learning/experience effect on choosing optimal information. However, the categorical variable "Position" in the logit regressions provides interesting insights. First, Group Position 2 (G2) is significantly positive meaning subjects at position G2 choose private information more frequently. Second, the coefficient of Group Position 3 (G3) is significantly negative (and even more negative compared with the coefficient on G2) indicating the tie neglect effect. Third, the coefficient of Group Position 4 (G4) is close to the coefficient of Group Position 2 (G2), suggesting similar frequencies of optimal information choices at G2 and G4.

Finding 10. *Subjects with higher CRT scores choose optimal information more frequently, while subjects with business major and high scores on "Theory of Mind" factor choose the optimal information less frequently.*

Individual Characteristics and Information Compliance

We also test whether individual characteristics can explain how the information is used. Our OLS regression has a dependent variable "Totalfollowinfo", which

	Dependent Variable					
	Total No. Optimal Info			Optimal Info		
	OLS	OLS	OLS	Logit	Logit	Logit
DFemale	-0.18	0.96	1	-0.04	0.24	0.24
	(0.73)	(0.66)	(0.69)	(0.19)	(0.19)	(0.19)
Age	0.04	0.05	0.02	0.01	0.01	0
	(0.04)	(0.07)	(0.07)	(0.01)	(0.02)	(0.02)
DReverse	-0.33	0.74	0.66	-0.07	0.19	0.17
	(0.85)	(0.72)	(0.81)	(0.19)	(0.18)	(0.18)
CRT		0.83*	0.80*		0.20**	0.20**
		(0.43)	(0.43)		(0.09)	(0.09)
DEcon		1.85	1.44		0.46	0.34
		(2.24)	(2.45)		(0.49)	(0.49)
DBuss		-3.75*	-4.03*		-0.81*	-0.90**
		(2.16)	(2.13)		(0.47)	(0.43)
DTech		1.84	1.44		0.47	0.37
		(2.22)	(2.32)		(0.45)	(0.44)
DSocial		-0.16	-0.24		-0.04	-0.07
		(1.83)	(1.95)		(0.39)	(0.38)
Factor1			0.36			0.09
			(0.42)			(0.09)
Factor2			-0.2			-0.05
			(0.36)			(0.09)
Factor3			-0.83**			-0.20**
			(0.37)			(0.09)
Factor4			-0.14			-0.04
			(0.48)			(0.10)
Time				0	0	0
				(0.01)	(0.01)	(0.01)
Experience				0.00	0.00	0.00
				(0.03)	(0.03)	(0.03)
Group Position 2				0.61***	0.63***	0.64***
				(0.17)	(0.18)	(0.18)
Group Position 3				-1.33***	-1.40***	-1.42***
				(0.19)	(0.20)	(0.20)
Group Position 4				0.67**	0.69**	0.70**
				(0.28)	(0.29)	(0.30)
Constant	16.14***	13.44***	14.31***	0.74*	0.12	0.37
	(1.16)	(3.06)	(3.24)	(0.38)	(0.77)	(0.74)
Observations	128	128	128	3072	3072	3072
F test/Wald test p	0.73	0.00	0.00	0.00	0.00	0.00

Baseline: male non-student subjects in P2 of the "PG" treatment. By definition, subjects in position 1 do not have choices over information, and thus not in the regression table.
In OLS regressions, standard errors are clustered by each unique group of 4 subjects; in logit regressions, standard errors are clustered for each subject. $p < 0.1$, *; $p < 0.05$, **; $p < 0.01$, ***.

Table 3.6: Optimal Info Choice and Individual Characteristics

equals the number of times when the observed information is followed (ICI). We exclude observations of G3 as it is not clear how to interpret the use of social information in case of a tie. As Table 3.7 shows, CRT is significantly positively correlated with the tendency to follow information. Also, information compliance rate is similar across different positions.

A logistic regression on a dummy variable "Dfollowinfo" (which is equal to 1 when the observed information is followed) suggests learning effects. Both Time and Experience variables are significantly correlated with the dependent variable. The effect of time is positive, suggesting that subjects choose a better strategy (follow information) as the game proceeds. But the significant negative effect of experience is surprising. After conducting a logistic regression with experience being a categorical variable (see Appendix B), we attribute this significant negative effect of experience is mainly due to subjects following their information at the first time in a specific position, and deviating afterwards. Given the significant effect of time, we also conduct the random effect model and find that, consistently with OLS, subjects with higher CRT follow information more frequently.

	Dependent Variable					
	Total No.	Follow Info		Follow Info		
	OLS	OLS	OLS	Logit	Logit	Logit
Dfemal	-0.52	-0.12	-0.19	-0.24	-0.02	-0.07
	(0.68)	(0.63)	(0.63)	(0.29)	(0.30)	(0.28)
Age	0.02	-0.03	-0.03	0.02	0	0
	(0.03)	(0.04)	(0.04)	(0.02)	(0.02)	(0.02)
DReverse	-0.2	0.21	0.29	0.21	0.36	0.37
	(0.7)	(0.7)	(0.66)	(0.27)	(0.27)	(0.26)
CRT		0.85**	0.87**		0.32**	0.31**
		(0.36)	(0.33)		(0.14)	(0.13)
DEcon		-2.1	-2.86		-1.33	-1.64*
		(1.50)	(1.84)		(0.82)	(0.92)
DBuss		-2.53	-3.35*		-1.51*	-1.81**
		(1.53)	(1.96)		(0.80)	(0.91)
DTech		-3.17**	-3.91**		-1.47*	-1.80*
		(1.51)	(1.89)		(0.85)	(0.98)
DSocial		-2.80**	-3.63**		-1.49**	-1.87**
		(1.25)	(1.68)		(0.75)	(0.90)
Factor1			-0.57			-0.21*
			(0.34)			(0.11)
Factor2			-0.09			0.06
			(0.33)			(0.14)
Factor3			-0.36			-0.22*
			(0.31)			(0.13)
Factor4			-0.38			-0.19
			(0.34)			(0.13)
Time				0.02**	0.02**	0.02**
				(0.01)	(0.01)	(0.01)
Experience				-0.17***	-0.17***	-0.17***
				(0.03)	(0.04)	(0.04)
Pair Position 2				-0.02	-0.02	-0.02
				(0.16)	(0.16)	(0.16)
Group Position 1				0.10	0.09	0.10
				(0.18)	(0.18)	(0.18)
Group Position 2				0.18	0.18	0.18
				(0.18)	(0.18)	(0.18)
Group Position 4				0.06	0.07	0.07
				(0.20)	(0.20)	(0.20)
Constant	27.50***	29.91***	30.71***	2.14***	3.44***	3.97***
	(1.3)	(1.96)	(2.31)	(0.56)	(1.09)	(1.2)
Observations	128	128	128	3840	3840	3840
F test/Wald test p	0.72	0.00	0.01	0.00	0.00	0.00

Baseline: male non-student subjects in P1 of the "PG" treatment.
Because "following information" is subject to different interpretations at position 3 as subjects may face a tie seeing social information, thus it is excluded from our main regression table.
In OLS regressions, standard errors are clustered by each unique group of 4 subjects; in logit regressions, standard errors are clustered for each subject. $p < 0.1$, *; $p < 0.05$, **; $p < 0.01$, ***.

Table 3.7: Information Compliance and Individual Characteristics (G3 excluded)

3.7 Conclusion

Our experiment modifies the standard sequential social learning setting. Subjects have to choose to observe either a private signal or the decisions made by earlier subjects in the sequence, rather than having both forms of information supplied by default. Compared with standard sequential social learning setting, our experiment enables us to conduct within-subject analysis of individual heterogeneity in information bias.

Our findings confirm that the individual heterogeneity identified in Duffy et al. (2017) exists in a sequential social learning environment. Again there are herd animals biased against private information, lone wolves who are biased toward it and subjects who behave optimally. In aggregate, there is no overall bias for or against private information. In other words, when mistakes can run both ways, they indeed run both ways. Also, it should be noted that social learning is in general successful. Most subjects switch from choosing private information to social information in later positions where they should learn from others.

Efficiency concerns can be one explanation why subjects are biased towards private information. Our results indicate that when a subject's decision can be observed by followers, she chooses private information more frequently. By choosing and revealing private information, one can help the followers in terms of better social information.

Another interesting finding of our experiment is the existence of "tie neglect" and confusion/mistakes. Many subjects wrongly believe that two heads are better than one in our social learning game without realizing the fact that two heads may disagree with each other. In addition, more than 2/3 of the subjects contradict their information at least once. This finding challenges the validity of many earlier studies where confusion/mistakes made by subjects cannot be explicitly detected.

The relationship between subjects' behaviour and their individual characteristics provides valuable insights. Among the major characteristics, CRT seems to be a very good indicator of subjects' behaviour. Subjects with higher CRT scores choose optimal information more frequently and follow information more frequently. In addition, subjects' individual traits may explain their behaviour in the lab intuitively.

One potential criticism of this paper is the lack of external validity because the real world decision-making environment is hugely simplified in the lab. Our experimental design follows existing literature in social learning experiment closely and the validity and limitation of lab experiments is discussed in Roe & Just (2009).

In brief, heterogeneity in information bias is observed in a sequential social learning environment. We believe our findings have important practical implications. An intuitive extension is mechanism design. In situations where a social planner can determine the sequence of decision making, lone wolves should be positioned at the beginning of the sequence and herd animals should never be positioned earlier in the sequence. Alternatively, it is also possible that with the existence of lone wolves and herd animals, an endogenously formed sequence can be self-enforcing efficient as herd animals and rational individuals may choose to be in later positions to wait for social information. Lone wolves, on the other hand, prefer to be the leaders in the sequence if waiting is costly. We leave this for future research.

Appendices

A Order Effect

As Table 3A.8 shows, there is no difference in information choices between "GP" and "PG" treatments at position 2 in both "Pair" and "Group" formations. Subjects in "GP" treatment are more likely to choose social information at position G3 (Mann-Whitney $p < 0.01$) and G4 (Mann-Whitney $p < 0.1$). This might be due to subjects in "PG" treatment having longer exposure to others' "trembling hands" (mistakes) in the "Pair" formation before they moved to more complex "Group" formation. However, subjects in both treatments show a very similar pattern of information choice – the frequency of choosing social information increases at later positions. Figure 3A.1 shows the distributions of information choices for each treatment. There are no significant differences between the two distributions (two-sample Kolmogorov-Smirnov test $p = 0.84$). In other words, there is no systematic order effect on the total number of private information choice. Together with the regression results in Section 3.6.2, there is no significant systematic order effect.

	Percentage of Social Information Chosen		
	"GP" Treatment	**"PG" Treatment**	**Mann-Whitney p-value**
"Pair"			
P1	N/A	N/A	N/A
P2	27.3	27.9	0.87
"Group"			
G1	N/A	N/A	N/A
G2	18.0	16.4	0.57
G3	64.1	54.2	0.01
G4	86.2	81.0	0.05

Table 3A.8: Information Choices by Treatment

B Effect of Experiences

Figure 3A.2 suggests that the negative significant effect of the experience reported in Table 3.7 is due to subjects changing their behaviour after the first time they experience a specific position in the sequence. Furthermore, results of the panel analysis in Table 3A.9 suggest that overall experience ("Time") is significant. The random effect model confirms the positive effect of CRT on complying with information. While there is an interesting dynamics of complying with information with experience, there is no significant learning in choosing information.

	Dependent Variable:		
		Dfollow	
		Logit	
DFemale	-0.24	-0.02	-0.07
	(0.29)	(0.30)	(0.28)
Age	0.02	0	0
	(0.02)	(0.02)	(0.02)
DReverse	0.22	0.37	0.38
	0.26	0.26	0.25
Time	0.02**	0.02**	0.02**
	(0.01)	(0.01)	(0.01)
Experience=2	-0.54***	-0.55***	-0.55***
	(0.19)	(0.19)	(0.19)
Experience=3	-0.50***	-0.50***	-0.51***
	(0.19)	(0.19)	(0.19)
Experience=4	-0.62***	-0.63***	-0.64***
	(0.21)	(0.21)	(0.22)
Experience=5	-0.99***	-1.00***	-1.01***
	(0.24)	(0.24)	(0.24)
Experience=6	-0.95***	-0.96***	-0.97***
	(0.20)	(0.20)	(0.20)
CRT		0.32**	0.31**
		(0.14)	(0.13)
DEcon		-1.33	-1.64*
		(0.82)	(0.92)
DBuss		-1.51*	-1.81**
		(0.80)	(0.91)
DTech		-1.47*	-1.81*
		(0.85)	(0.98)
DSocial		-1.49**	-1.87**
		(0.75)	(0.90)
Factor1			-0.21*
			(0.11)
Factor2			0.06
			(0.14)
Factor3			-0.22*
			(0.13)
Factor4			-0.19
			(0.13)
Constant	2.20***	3.50***	4.03***
	0.58	1.09	1.2
Observations	3840	3840	3840
Wald Test p	0.00	0.00	0.00

Logit regressions standard errors are clustered by subject. $p < 0.1$, *; $p < 0.05$, **; $p < 0.01$, ***.

Table 3A.9: Information Compliance and Individual Characteristics (Logit)

	Dependent Variable:		
	Dfollow		
	xt-Logit (Random Effect)		
	(1)	(2)	(3)
DFemale	-0.36	-0.07	-0.11
	(0.33)	(0.34)	(0.34)
Age	0.03	0.01	0.01
	(0.03)	(0.03)	(0.03)
DReverse	0.35	0.59*	0.59*
	(0.3)	(0.31)	(0.3)
Experience=2	-0.56**	-0.56**	-0.56**
	(0.24)	(0.24)	(0.24)
Experience=3	-0.47*	-0.47*	-0.47*
	(0.24)	(0.24)	(0.24)
Experience=4	-0.56**	-0.56**	-0.56**
	(0.24)	(0.24)	(0.24)
Experience=5	-0.92***	-0.92***	-0.92***
	(0.23)	(0.23)	(0.23)
Experience=6	-0.82***	-0.82***	-0.82***
	(0.23)	(0.23)	(0.23)
CRT		0.44***	0.42***
		(0.14)	(0.14)
DEcon		-1.39	-1.55
		(1.08)	(1.05)
DBuss		-1.65	-1.81*
		(1.10)	(1.07)
DTech		-1.68	-1.87*
		(1.07)	(1.04)
DSocial		-1.66	-1.89*
		(1.01)	(0.99)
Factor1			-0.23
			(0.15)
Factor2			0.08
			(0.16)
Factor3			-0.20
			(0.16)
Factor4			-0.18
			(0.17)
Constant	3.08***	4.30***	4.50***
	(0.73)	(1.44)	(1.42)
Observations	3840	3840	3840
Wald Test p	0.00	0.00	0.00

Panel variable is each subject and time variable is Time with range [1, 36]. $p < 0.1$, *; $p < 0.05$, **; $p < 0.01$, ***.

Table 3A.10: Information Compliance and Individual Characteristics (Random Effects)

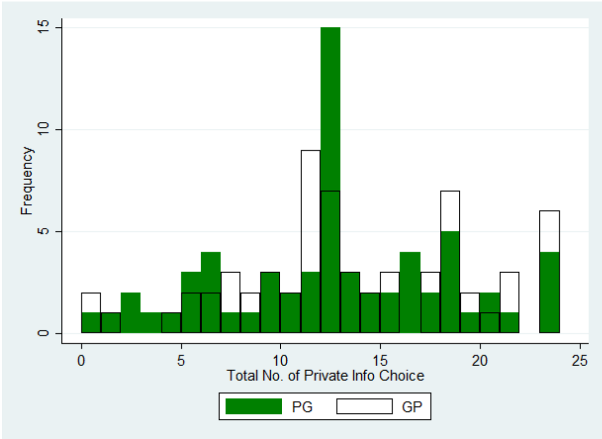

Figure 3A.1: Distributions of TPI by Treatment

TPI in "PG" (green) and "GP" (white) treatments. N of subjects = 64 in each treatment.

Figure 3A.2: Experience Effect in "Group" Formation

The x-axis represents Experience from 1 to 6, the y-axis - the average percentage. Top Left: The dynamics of information choices at G2, G3 and G4. Top Right: The dynamics of following the social information at G2, G3 and G4. 170 cases of a tie at G3 are excluded from the calculation. Bottom Left: The dynamics of following the private information at G1, G2, G3 and G4.

C Individual Traits Questions

Answer options (coded 1-6, respectively): "Never", "Almost Never", "Sometimes", "Frequently", "Almost Always", and "Always" . The order of questions was scrambled. Due to internal inconsistency, questions 27-30 were excluded, as well as "Trust" motive due to marginal internal consistency ($\alpha = 0.68$) and no significant effect of inclusion on the results. "Code" identifies factor loading in Table 3A.12.

No.	Question	Motive	Mean (SD)	Alpha	Code
1	Behave unconventionally.[a]	Contradictory (+)	3.23 (1.07)	0.825	zqct2
2	Take the opposite route from everyone else.[b]	Contradictory (+)	3.38 (0.93)		zqct3
3	Run against the crowd.	Contradictory (+)	3.3 (0.98)		zqct4
4	Am at ease when behaving differently from others.[b]	Contradictory (+)	3.74 (1.24)		zqct5
5	Follow others to avoid being the only one making a mistake.	Contradictory (-)	2.73 (0.95)		zqct6
6	Do what others do rather than rely on my opinion.	Contradictory (-)	2.53 (0.78)		zqct7
7	Ignore my own gut feeling and instead follow other people.[b]	Contradictory (-)	2.7 (0.81)		zqct8
8	Find it easier to follow others than to search for my own path.[a]	Contradictory (-)	2.65 (0.97)		zqct9
9	Feel better with a loss when everyone else lost as well.	Social Regret (+)	4.05 (1.22)	0.747	zqsr1
10	Feel better when losing in a group than losing alone.	Social Regret (+)	4.09 (1.27)		zqsr3
11	Regret my mistakes less when others made the same choice.	Social Regret (+)	3.91 (1.11)		zqsr4
12	Understand how others think.[b]	Theory of Mind (+)	3.9 (1.11)	0.785	zqtm1
13	Able to explain others' behavior.[b]	Theory of Mind (+)	3.77 (0.98)		zqtm2
14	Feel I am not good at understanding others' behavior.[b]	Theory of Mind (-)	2.77 (1.04)		zqtm3
15	Drawn to compete with others.[a]	Rivalry (+)	3.61 (1.13)	0.765	zqrv3
16	Feel that I must win at everything.[a]	Rivalry (+)	3.16 (1.57)		zqrv4
17	Feel that winning or losing doesn't matter to me.[a]	Rivalry (-)	3.07 (1.12)		zqrv1
18	Feel sympathy for those who are less fortunate than me.[a]	Altruism (+)	4.65 (1.02)	0.691	zqal3
19	Love to help others.[a]	Altruism (+)	4.48 (1.12)		zqal4
20	Try not to do favors for others.[a]	Altruism (-)	2.16 (0.87)		zqal2
21	Feel indifference to others' misfortunes.[a]	Altruism (-)	2.41 (1.10)		zqal1
	EXCLUDED Questions				
22	Trust in others doing the job well.	Trust (+)	3.54 (1.00)		zqtr1
23	Believe that others have good intentions.[c]	Trust (+)	4.04 (0.96)		zqtr2
24	Feel that others don't know what they are doing.[b]	Trust (-)	3.36 (0.98)		zqtr3
25	Doubt others' abilities or intentions.[b]	Trust (-)	3.23 (0.94)		zqtr4
26	Suspect hidden motives in others.[c]	Trust (-)	3.45 (1.08)		zqtr5
27	Feel uncomfortable to do things differently from the group.[b]	Social Regret (+)	2.84 (0.95)		zqsr5
28	Before I make a choice, I try to find out what other people choose.	Social Regret (+)	3.46 (1.01)		zqsr2
29	Feel confused about why people do what they do.	ToM (-)	3.61 (1.21)		zqtm4
30	Avoid situations involving competition.[a]	Rivalry (-)	2.99 (1.15)		zqrv2

Sources: (a) Duffy and Kornienko (2010); (b) Duffy et al (2016); (c) Costa and McCrae (1992).

Table 3A.11: Individual Traits Questions

Code	Factor1	Factor2	Factor3	Factor4	Uniqueness
zqct2	0.5501	0.2437	-0.1758	0.1448	0.5862
zqct3	0.6648	0.1779	0.1006	0.2101	0.4721
zqct4	0.7138	0.2412	-0.0765	0.1606	0.4006
zqct5	0.5365	-0.0037	0.0083	0.1842	0.6781
zqct6	-0.6498	0.3511	0.054	0.1056	0.4404
zqct7	-0.7313	0.1105	0.002	0.198	0.4137
zqct8	-0.553	0.2796	0.0559	0.0922	0.6044
zqct9	-0.5858	0.146	0.0271	0.0801	0.6283
zqsr1	-0.1891	0.6256	0.3612	-0.1933	0.405
zqsr3	-0.2106	0.5135	0.3851	-0.0878	0.5359
zqsr4	-0.1578	0.5535	0.2905	-0.0587	0.5808
zqtm1	0.2443	-0.0104	0.6699	0.371	0.3538
zqtm2	0.2188	-0.0386	0.7025	0.3139	0.3587
zqtm3	-0.0632	0.2204	-0.5217	-0.0954	0.6662
zqrv3	0.389	0.5137	-0.0045	-0.28	0.5063
zqrv4	0.2869	0.5194	0.0084	-0.1992	0.6081
zqrv1	-0.2996	-0.4971	0.2179	0.2721	0.5416
zqal3	0.1174	-0.0728	0.3512	-0.503	0.6046
zqal4	0.1155	-0.2661	0.3343	-0.382	0.6582
zqal2	-0.0431	0.3885	-0.1838	0.3507	0.6904
zqal1	0.0504	0.4674	-0.2966	0.2919	0.6059

Table 3A.12: Factor Loadings

D Robustness Check

As the range of our variables is limited, we checked whether our results of Table 3.6 and Table 3.7 are robust to censoring.

	Dependent Variable:				
	Total No. of Optimal Info				
	(1)	(2)	(3)	(4)	(5)
DFemale	-0.11	0.77	0.74	1.21*	1.28*
	(0.76)	(0.79)	(0.77)	(0.71)	(0.73)
Age	0.04	0.04	0.08	0.05	0.02
	(0.04)	(0.05)	(0.06)	(0.07)	(0.07)
DReverse	-0.4	0.14	0.46	0.78	0.72
	(0.92)	(0.83)	(0.76)	(0.76)	(0.84)
CRT		1.23***		0.93**	0.91**
		(0.40)		(0.46)	(0.45)
DEcon			3.74*	2.37	1.94
			(2.17)	(2.42)	(2.56)
DBuss			-2.65	-3.83*	-4.09*
			(1.97)	(2.20)	(2.11)
DTech			3.93**	2.11	1.7
			(1.92)	(2.33)	(2.40)
DSocial			0.74	-0.16	-0.2
			(1.68)	(1.88)	(1.96)
Factor1					0.41
					(0.44)
Factor2					-0.12
					(0.38)
Factor3					-0.90**
					(0.39)
Factor4					-0.15
					(0.50)
Constant	16.41***	14.02***	13.10***	13.19***	14.01***
	(1.27)	(1.45)	(2.96)	(3.19)	(3.31)
Observations	128	128	128	128	128
F-Test p	0.79	0.04	0.00	0.00	0.00

Tobit regressions with lower limit of 0 and upper limit of 24.
Baseline: male non-student subjects in P2 of the "PG" treatment.
Standard errors are clustered by groups of 4 subjects. $p < 0.1$, *; $p < 0.05$, **; $p < 0.01$, ***.

Table 3A.13: Optimal Information Choice and Individual Characteristics

	Dependent Variable:				
	Total No. of Follow Info				
	(1)	(2)	(3)	(4)	(5)
DFemale	-0.75	0.09	-0.68	-0.19	-0.33
	(0.91)	(0.99)	(0.81)	(0.82)	(0.84)
Age	0.06	0.05	0.02	-0.03	-0.03
	(0.07)	(0.08)	(0.06)	(0.07)	(0.07)
DReverse	-0.03	0.68	0.01	0.79	0.83
	0.9	0.93	0.87	0.93	0.86
CRT		1.24***		1.51***	1.53***
		(0.44)		(0.53)	(0.48)
DEcon			-2.64	-4.46	-5.26
			(3.07)	(3.04)	(3.40)
DBuss			-4.05	-5.90*	-6.85*
			(3.14)	(3.17)	(3.59)
DTech			-3.84	-6.68**	-7.43**
			(3.02)	(3.04)	(3.37)
DSocial			-4.45	-5.55*	-6.53*
			(3.04)	(2.94)	(3.33)
Factor1					-0.74
					(0.48)
Factor2					-0.19
					(0.47)
Factor3					-0.42
					(0.42)
Factor4					-0.53
					(0.41)
Constant	27.53***	25.60***	32.39***	32.64***	33.65***
	(2.06)	(2.34)	(3.77)	(3.76)	(4.15)
Observations	128	128	128	128	128
F-Test p	0.65	0.02	0.50	0.02	0.05

Tobit regressions with lower limit of 0 and upper limit of 30.
Baseline: male non-student subjects in P2 of the "PG" treatment.
Standard errors are clustered by groups of 4 subjects. $p < 0.1$, *; $p < 0.05$, **; $p < 0.01$, ***.

Table 3A.14: Information Compliance and Individual Characteristics

CHAPTER 4 A MODEL OF MOTIVATED OVERCONFIDENCE

4.1 Introduction

The prevalence of overconfidence is widespread and robust.[1] Overconfidence and its consequence on economic activities have been addressed by economists since Adam Smith, who noted that "The over-weening conceit which the greater part of men have of their own abilities, is an ancient evil remarked by the philosophers and moralists of all ages."(Smith 1776, Book I). Such "ancient evil" still concerns modern economists, as DeBondt & Thaler (1995) point out that the prevalence of overconfidence is "perhaps the most robust finding in the psychology of judgement". Overconfident beliefs may lead to suboptimal decisions in many ways. Daniel Kahneman remarks that overconfidence is "the most damaging" among the various flaws that bedevil decision-making (see, Shariatmadari, 2015).

In economics, researchers care not only how overconfidence affects decision makers, but also about the motives behind. In general, two intrapersonal motives have been proposed to explain the widely observed overconfident behaviour. The first intrapersonal motive argues that self-image concerns asymmetrically affect the interpretation of information about one's abilities, and this asymmetry can lead to overconfidence. In other words, people prefer to inflate the beliefs about their own ability simply for the consumption value of holding high beliefs about themselves (Bénabou & Tirole, 2002; Kőszegi, 2006). Through the same channel, patients may be reluctant to see a doctor in order to maintain a positive view of one's health and to avoid potential health anxiety (Kőszegi, 2003). Benoît & Dubra (2011) propose that one possible mechanism for individuals to achieve inflated beliefs is through asymmetric seeking/updating information. People with low self-assessment tend to keep seeking information about their ability as long as there is a chance for improvement, on the other hand, they stop searching for information when there is little room to update their beliefs upward.

The second intrapersonal motive suggests that overconfidence is instrumental in dealing with self-control problems. The primary argument is that confidence in

[1] The term overconfidence is used broadly by psychologists and economists, referring to both over-optimism and over-precision (Grubb, 2015). Overoptimistic people overestimate their own abilities or prospects, in absolute terms or in comparison to others. In contrast, over-precision describes the phenomena that people place overly narrow confidence intervals around their forecasts. In this paper, overconfidence is used interchangeably as over-optimism.

ones ability or chances of success is a compelling motivator to conduct and persevere in challenging tasks or long-term projects. These models (e.g. Carrillo & Mariotti, 2000; Bénabou & Tirole, 2002) assume the existence of self-control problem (or "weakness of will") and its corresponding negative welfare consequences (e.g. insufficient saving and suboptimal level of effort). Overconfidence thus can serve as a commitment tool to handle the self-control issue: by believing exerting effort brings a greater future payoff, agents become less vulnerable to current temptation. Agents with "weakness of will" in these models are essentially similar to individuals with hyperbolic discounting preference (Laibson, 1997). For example, to motivate oneself to save more, the agent may choose to hold an inflated belief about the real return of saving.

Although it is beyond the scope of the present paper, Bénabou & Tirole (2002) and Burks et al. (2013) suggest that overconfidence might be a result of interpersonal social signalling. Since people care about what others would think of them, overconfidence is driven by the motive to send positive signals to others about their ability. Therefore, overconfidence might be a socially rooted bias. However, it should be noted that there is no definite evidence to suggest whether interpersonal overconfidence is a direct result of biased updating or strategical misleading (Burks et al., 2013).

The current paper develops an intrapersonal overconfidence model based on the classical models by Bénabou & Tirole (2002) and differs in two key features. First, I introduce a waiting stage where agents are no longer able to change the already exerted effort level but still need to wait for the payoff. Such situation is common in real life, for example, it is common to wait for exam/application/journal submission results for a long time. Second, I propose a quadratic cost for distorting beliefs (compared to the fixed cost in previous models). More extreme deviations are increasingly more costly to hold in this model, and the existence of such physical/mental costs explain the fact that in reality, wild beliefs are not typical. With these modifications, this model predicts that in equilibrium, the agent holds a dynamic pattern of overconfident belief across time. Specifically, people are most overconfident when starting a project, the confidence level gradually diminishes over time, and a discontinuous decrease is expected after the submission of the work. Then during the waiting period, the confidence continues to decline until the date of result realisation. Our model suggests that overconfidence should not be treated as a static fact. Instead, people's expectation about future outcomes depends critically on the timing.

4.2 Related Literature

In this section, I present a selective review of the existing literature. In the first part, the empirical and experimental evidence on overconfidence found by economists and psychologists is presented. Then I provide a selective review of the theoretical models explaining the motives of overconfidence.

4.2.1 The Existence of Overconfidence

In the social psychology literature, overconfidence has had a prominent position for many decades. Baumhart (1968) finds that business people believe that they have better business ethics practice that others. Larwood & Whittaker (1977) conclude that management students and corporate presidents hold a self-serving bias of their own competence and consistently overestimate their abilities in sales and marketing environment. Langer (1975) suggests that people often experience “illusion of control” when playing a game of chance. They feel as if they can control the next roll of the dice and thus overestimate the probability of success. A famous study by Svenson (1981) suggests that in an experiment, 83 percent of American subjects think that they were in the top 30 percent regarding driving safety and skills. Similarly, the “Lake Wobegon effect” or “better than average effect” that everyone believes that she is above average have been supported by many studies (Cannell, 1988; Brown, 2012).

The prevalence of overconfidence in economic activities is supported by economists. There is a growing literature studying the behaviour of overconfident CEOs, investors, and consumers. Malmendier & Tate (2005) draws implications from observing when CEOs choose to exercise their stock options. They find that CEOs are not exercising their options timely so that they are under-diversified concerning their own company-specific risk. Otto (2014) measures CEO overconfidence by studying the gap between firm’s voluntary earnings forecasts and the realised earnings. In finance, the active investing puzzle refers to the phenomena that individual investors often engage in excessive trading activities. The more active investors are, the more they typically lose (Odean, 1999). Evidence suggests that overconfidence provides a natural explanation for the active investing puzzle since overconfident investors trade more aggressively in the face of transactions costs and negative expected payoffs (Odean, 1998). This claim is further supported by studying the gender difference in trading behaviour. Based on the robust psychological finding that men are more overconfident than women[2], Bar-

[2] For example, see Deaux & Farris (1977) and Lundeberg et al. (1994). Lundeberg et al.

ber & Odean (2001) find clear evidence that males are trading more actively than females.

Overconfidence about self-control ability is a leading explanation for why consumers overpay for gym memberships that they underutilise. Overconfident individuals overestimate their self-control ability and thus overweight the membership benefit and avoid paying for per-visit gym fees. However, based on the actual number of visits, a significant proportion of consumers can be better off by not signing up gym membership (just pay a per-visit fee instead) (DellaVigna & Malmendier, 2006). Experimental results suggest that individuals are over-optimistic about the likelihood of redeeming rebates (Silk, 2004). Many subjects choose the long-term larger payment over immediate cash in the lab but forget to claim later (Ericson, 2011). According to Grubb & Osborne (2014), many consumers select the suboptimal mobile plan due to overconfidence. Thus facing overconfident consumers, firms have an incentive to complicate their contracts or distort marginal prices and product quality to exploit the mistake (Grubb, 2015).

A natural question is why overconfidence does not die out with learning. Researchers have found evidence of different perspectives indicating that learning is often challenging and inefficient in reality. Since firms have no incentive to de-bias consumers, consumers are unlikely to receive information for learning (Gabaix & Laibson, 2006). Experimental evidence by Subbotin (1996) suggests that even outcome feedback is available, consumers often respond ineffectively in practice. The persistence of overconfidence may also be enhanced by the fact that different behavioural biases may reinforce each other. For example, the theory of cognitive dissonance by Festinger (1962) suggests that people experience stress when confronted with information that contradicts existing beliefs, and thus try to avoid such belief-changing information. Behavioural CEOs thus may choose to learn insufficiently to sustain a high self-esteem generated from past success. CEO overconfidence may also be strengthened by self-attribution bias. Self-attribution bias suggests people regard successful outcomes as a result of their own skill but blame unsuccessful results on luck (Shefrin, 2002). It also can explain the active investing puzzle as investors who have achieved high returns attribute the success to their high trading skill and become increasingly overconfident, while investors who experience low returns attribute it to bad luck and do not adjust their overconfidence level (Gervais & Odean, 2001). Cursedness,

(1994) also indicates that such gender difference is task specific and Prince (1993) finds that men are more overconfident than women in financial oriented tasks.

an equilibrium concept developed in Eyster & Rabin (2005), is another reason behind the persistence of overconfident investors. The inability of learning from other people's actions leads to overweighting private overconfident judgement in decision-making. A cursed investor underweights the information implicit in the actions of others, and hence trades readily in the financial market (Eyster et al., 2015).

On the other hand, the difficulty of learning is challenged by several recent studies. Hoelzl & Rustichini (2005) shows that the alleged persistence of overconfidence depends critically on the ambiguity of the traits evaluated and on the monetary incentives. Subjects are learning more effectively when financial incentives are presented. Similarly, in J. Clark & Friesen (2009), the individual overconfidence for both relative and absolute self-assessments is eliminated in a real effort task once monetary incentives and timely feedback are provided. Another stand of theories suggests that the persistence of overconfidence is indeed an equilibrium. In other words, people are motivated to hold overconfident beliefs about themselves. In the following part, I briefly describe three primary motives proposed by economists: social signal, consumption and self-efficacy.

4.2.2 The Causes of Overconfidence

Burks et al. (2013) experimentally test three mechanisms that produce overconfidence: Bayesian updating (Benoît & Dubra, 2011), concern for ego utility (Kőszegi, 2006) and social signalling. They reject the first two mechanisms and argue that overconfidence is likely to be a social signalling bias. The idea of socially rooted overconfidence is initially proposed by several psychologists and economists. For example, the sociometer theory suggests that self-esteem is primarily developed to motivate people to behave in ways that sustain their connections with other people (Leary et al., 1995). Therefore, people choose to be overconfident to boost self-esteem to achieve higher relational value from social interaction. Bénabou & Tirole (2002) focus on the strategic interaction aspect of being overconfident. Believing oneself to be of high ability makes it much easier to convince others that one indeed is competent. In other words, to lie most convincingly one must believe her own lies. In a classical bargaining experiment, Proeger & Meub (2014) find that overconfidence in individualistic setting does not persist. However, the introduction of a basic observational social setting fosters overconfident self-assessments. Through the lens of tournament experiments, Charness et al. (2014) find that overconfidence is motivated at least partly by strategic considerations. Also, subjects may be unconscious about the emergence of overconfidence in the strategic environment. Ewers & Zimmermann (2015) find that the reported performance measure on quiz questions submitted by subjects is significantly higher when an audience presents. They argue that overconfidence might be a consequence of social approval seeking. Thoma (2016) experimentally confirms the social roots of overconfidence through Raven Matrix tournaments. She finds that subjects, especially male subjects, inflate or deflate their self-assessment strategically in response to the social environment.

The self-image and anticipatory utility argument for overconfidence indicates that since people derive ego utility from positive views about the self (current and future), there is an incentive to hold overconfident beliefs about their abilities or future income (Kőszegi, 2006; Weinberg, 2009; Kőszegi, 2010). In brief, when beliefs directly affect utility, people tend to hold overconfident beliefs. Kőszegi (2006) shows that biased views can emerge purely from ego utility and without the necessity of biased information processing in most previous literature. He also suggests that the agent manages her self-image by distorting financial choices relative to her present beliefs. Weinberg (2009) identifies conditions under which a rational, time-consistent agent prefers to overestimate his ability. In his model, individuals care about their beliefs about their ability in a risk averse manner. Risk aversion over ability leads people to limit their learning about their actual ability to sustain an inflated view of themselves. Before the above two studies, there are two strands of non-Bayesian models that predict overconfident self-views. In one set, individuals directly choose their beliefs and prefer to become moderately overconfident rather than exactly accurate to make themselves feel better (Akerlof & Dickens, 1982; Brunnermeier & Parker, 2005). In other models, biased views are generated from misinterpreting new information (Gervais & Odean, 2001). Eil & Rao (2011) conduct a laboratory experiment to test the correlation between belief-based utility and information processing and acquisition. Their findings suggest that self-esteem concerns lead people to update information asymmetrically. In brief, people update their beliefs consistent with Bayesian for good news and significantly discount bad news. Recent information avoidance literature suggests that people may actively choose to avoid bad news in the face of avoidance costs (Golman et al., 2017).

Overconfident beliefs also have a significant instrumental value, enhancing individuals' self-efficacy. Confidence in ones ability and chances of success is a strong motivator to undertake challenging tasks and persevere in long-term projects

(Bénabou & Tirole, 2016). The above argument depends critically on the assumption that people have imperfect willpower (self-control problem) and vulnerable to present temptations such as over-consuming or shirking. Overconfidence can be adopted as a commitment device to deal with the self-control problem: simply, people are more likely to work/save if they are optimistic about the outcome of the project/investment. Several seminal papers have contributed to the instrumental motive of overconfidence (Carrillo & Mariotti, 2000; Bénabou & Tirole, 2002, 2004). Although overconfidence as a commitment device is intuitively convincing, limited empirical evidence has been identified. Using data from the Survey of Consumer Finances, Puri & Robinson (2007) find that more optimistic people work harder and save more. However, the overconfidence of more successful individuals can also be explained by learning: previous success breeds over-optimistic beliefs (Malmendier & Taylor, 2015). In the next chapter of this thesis, I provide some empirical evidence supporting the significance of instrumental overconfidence.

4.3 Model

In this section, I develop a simple intrapersonal model of motivated overconfidence. In the benchmark model, neither the consumption motive nor the instrumental motive is considered (cognitive distortions are not possible), and then I nest the consumption motive and instrumental motive sequentially into the benchmark. A risk neutral agent i faces three periods. During the working period ($t = 1$), she works on a particular task and submits her work. Then she waits for the result during the waiting period ($t = 2$) and eventually, she reaps a final payoff during the realisation period ($t = 3$).

4.3.1 The Benchmark Model

In the benchmark model, the agent does not distort her belief, and the only choice variable is the level of effort. At $t = 1$, she decides on her effort level (e.g. hours of working) $e > 0$. Exerting effort is costly and the cost is $c \cdot e, c > 0$. The final payoff $V(\theta, e) = \theta \ln(e)$ depends on effort level e and ability $\theta > 0$. I assume that the agent knows her actual ability θ and the payoff function $V(\cdot)$.

At $t = 2$, she has finished her work and thus is no longer able to change e but there is still time waiting for result realisation. For simplicity, in this paper, I assume that the agent has a perfect memory about the amount of effort she exerted at $t = 1$ and she does not distort her memory.[3] At $t = 3$, she receives a final payoff $U_3 = V(\theta, e)$. Let $\omega_2 \geq 0$ and $\omega_3 \geq 0$ represent the weighting she puts on the waiting period and the realisation period respectively. In other words, ω_2 and ω_3 are the "awareness" parameter which measure to what extent the agent is aware of her future utility at $t = 2$ and $t = 3$. $\delta \in (0, 1]$, is the normal discounting parameter, which represents how patient the agent is. Let U_t represent the instantaneous utility, and U_t^T be the total utility at t. The agent is simply choosing the effort level, e, to maximise the present discounted utility at $t = 1$:

$$U_1 = -ce \tag{4.1}$$

In addition, the agent anticipates that:[4]

$$U_2^T = \omega_3 \delta U_3 \tag{4.2}$$

$$U_3^T = U_3 = \theta \ln(e) \tag{4.3}$$

Therefore, the agent chooses the level of effort to maximise the total utility $U_1^T = U_1 + \omega_2 \delta U_2^T + \omega_3 \delta^2 U_3^T$:

$$\arg\max_e \quad U_1^T = -ce + \omega_2 \delta U_2 + \omega_3 \delta^2 U_3 \tag{4.4}$$

The solution of equation (4.4) is:

$$e^B = \frac{\theta \delta^2 \omega_3 (1 + \omega_2)}{c} \tag{4.5}$$

The optimal level of effort in the benchmark model, e^B, has intuitive properties. First, it is positively determined by the agent's ability θ so that more competent agent works harder in the equilibrium. Second, the agent who cares more about future utility works more. $\delta \cdot \omega$, a combination of awareness and patience represents to what extend the agent cares about future utility. Third, the optimal level of effort is negatively correlated with the cost of effort.

The benchmark model has a straightforward prediction that the agent chooses

[3] In reality, it is possible that the individual may be motivated to have a selective memory (e.g. memorising good signals and forgetting bad ones (Chew et al., 2015)). However, in terms of behavioural outcomes selective memory can be equivalent to the belief distortions I introduce later (Bénabou, 2015).

[4] $U_2 = 0$ because at $t = 2$, the agent has submitted her work and cannot change her effort, while she is still away from payoff realisation. Thus, $U_2^T = U_2 + \omega_3 \delta U_3^T$. Given $t = 3$ is the final period, U_3^T is indeed equivalent to U_3, which equals $\theta \ln(e)$.

the optimal level of effort to maximise her present discounted utility. In the next parts, I extend it to include cognitive distortions from consumption and instrumental motives.

4.3.2 Consumption Motive

One source of cognitive distortion comes from the fact that the agent derives anticipatory feelings from thinking about the future payoff, and can be motivated to inflate her belief about the payoff to enjoy the positive feelings. Such cognitive distortions are denoted as *consumption* motive (also known as *affect-driven* motive in Bénabou (2015)). Let $s \cdot \tau_t \cdot X_t$ represent the anticipatory utility, where $s > 0$ is the savouring parameter representing the extent to which she cares about anticipatory feelings, $\tau_t \geq 0$ accounts for the time distance between t and the realisation date T and thus by definition, $\tau_1 > \tau_2 > \tau_3 = 0$. In other words, τ_1 is the sum of the length of period one t_1 and period two t_2, τ_2 is the length of period two t_2 only, $\tau_3 = 0$ as there is no distance between t_3 and T ($t_3 = T$). Therefore by construction, $\tau_1 > \tau_2 > \tau_3 = 0$. X_t represents her belief at t about the final payoff. Importantly, X_t does not necessarily equal $V(\cdot)$ since an agent can be motivated to hold a biased belief.[5] Consequently, in our model, the anticipatory utility is positively correlated with τ_t because there are more opportunities for savouring as waiting time increases (Bénabou, 2013, p. 434).

I assume that cognitive distortions are costly. Physical or mental costs are incurred while the agent tries to bias her belief about the payoff.[6] In my model, I introduce a quadratic cost on *payoff distortion* $\lambda(X_t - V(\theta, e))^2$, which depends on the degree of realism $\lambda > 0$ and the magnitude of distortion on payoff, $X_t - V(\theta, e)$. I use quadratic cost function (increasingly costly deviation) to capture the fact that as the desired beliefs are further away from reality, they are increasingly more difficult to be justified.[7] Such quadratic cost function also keeps the consumption motive in our model consistent with Brunnermeier & Parker (2005) that, small bias in beliefs leads to first-order gains in anticipatory utility and only second-order costs.

[5] Specifically, X_1 is the agent's expectation about the final reward at $t = 1$; X_2 is the agent's expectation about the final reward at $t = 2$ and X_3 is her expectation about the final reward just before realisation.

[6] Physical costs can be involved during the process of active information avoidance (Golman et al., 2017) and selective attention (Schwartzstein, 2014). Mental costs incur when an agent adopts mental strategies, such as biased searching through memory for justifications for desired beliefs (Kunda, 1990).

[7] Bracha & Brown (2012) provides a model for biased perception about risk with similar cost argument.

At $t = 1$ with consumption motive, the agent is choosing both effort and belief, $\{e, X_1\}$ maximising U_1^T:

$$\underset{\{e,\ X_1\}}{\arg\max} \quad U_1^T = \underbrace{s\tau_1 X_1 - \lambda(X_1 - \theta\ln(e))^2 - ce}_{U_1} + \omega_2\delta U_2^T + \omega_3\delta^2 U_3^T \tag{4.6}$$

Therefore, compared with the benchmark model, the agent now derives utility from anticipating the final payoff, $s\tau_1 X_1$ and simultaneously pays a belief distortion cost $\lambda(X_1 - \theta\ln(e))^2$. The same applies to U_2^T:

$$\underset{X_2}{\arg\max} \quad U_2^T = \underbrace{s\tau_2 X_2 - \lambda(X_2 - \theta\ln(e))^2}_{U_2} + \omega_3\delta U_3^T \tag{4.7}$$

The agent at $t = 2$ also derives utility from anticipation and thus can choose to bias her belief. Importantly, as $\tau_1 > \tau_2$, the agent savours less at $t = 2$ compared to $t = 1$. Consistent with the benchmark setup, the key difference between the second and first period is the choice of effort. At $t = 2$, effort e is already determined and exerted so she is no longer able to choose the level of effort at the waiting period.

At $t = 3$, there is no time nor opportunities left for savouring as $\tau_3 = 0$, therefore X_3 is a choice of the following:

$$\underset{X_3}{\arg\max} \quad U_3^T = \theta\ln(e) - \lambda(X_3 - \theta\ln(e))^2 \tag{4.8}$$

That is, at $t = 3$ the agent reaps a final payoff but there is no anticipatory utility and thus in equilibrium X_3^C is not distorted as shown in the following equation that $X_3^C = \theta\ln\big(e^C\big)$. Solving equation (4.6), (4.7) and (4.8) simultaneously, we get the intrapersonal equilibrium with consumption motive:

$$\begin{cases} e^C = \dfrac{s\theta(\tau_1 + \delta\tau_2\omega_2) + \theta\delta^2\omega_3(1 + \omega_2)}{c} \\[2ex] X_1^C = \dfrac{s\tau_1}{2\lambda} + \theta\ln\big(e^C\big) \\[2ex] X_2^C = \dfrac{s\tau_2}{2\lambda} + \theta\ln\big(e^C\big) \\[2ex] X_3^C = \theta\ln\big(e^C\big) \end{cases} \tag{4.9}$$

The intrapersonal equilibrium with consumption motive provides several important insights. First, compared with the benchmark model, the equilibrium level of effort, e^C, is higher since $e^C - e^B = \frac{s\theta(\tau_1+\delta\tau_2\omega_2)}{c} > 0$. In other words, the fact that one derives utilities from anticipation motivates the individual to work more. The magnitude of this effect is positively correlated with the savouring parameter s. On the other hand, consistent with the benchmark model, the equilibrium level of effort is positively determined by her ability, awareness and patience. If $s = 0$, $e^C = e^B$. Second, overconfident beliefs emerge. The equilibrium result predicts that the agent holds overconfident beliefs about the final payoff at $t = 1$ and $t = 2$ given $X_1^C - \theta\ln\left(e^C\right) = \frac{s\tau_1}{2\lambda} > 0$ and $X_2^C - \theta\ln\left(e^C\right) = \frac{s\tau_2}{2\lambda} > 0$. The emergence of overconfident beliefs is because the agent derives greater utility from more positive beliefs. The optimal degree of overconfidence is positively correlated with the savouring parameter s as the agent who derives more utility from savouring has greater incentive to be overconfident. Third, overconfident belief diminishes over time and converges to the unbiased level at the end of the waiting period. The drop in overconfidence from $t = 1$ to $t = 2$, $X_1^C - X_2^C = (\tau_1 - \tau_2)\frac{s}{2\lambda} > 0$, states the fact that overconfidence diminishes over time. In the end, just before result realisation, the belief reaches the unbiased level as $X_3^C = \theta\ln\left(e^C\right)$. This result is driven by the assumption that anticipatory utility diminishes over time, as less time available for savouring, the agent is less likely to costly inflates her belief.

Summary 1. Anticipatory utility leads to the emergence of overconfident beliefs. The agent who savours future payoffs more frequently works harder and holds more overconfident beliefs. The degree of overconfidence diminishes over time until the realisation of payoff, where her belief becomes unbiased.

Figure 4.1 shows the dynamic of overconfidence with the consumption motive.

4.3.3 The Self-control Problem and Instrumental Motive

The Weakness of Will

The above section illustrates the cognitive distortion from the anticipatory utility (consumption motive). In this section, I extend the benchmark model to allow for an alternative motive of distortion, the instrumental motive associated with the self-control problem. Self-control problems are prevalent and examples include problem drinking (Vuchinich & Simpson, 1998), obesity (Philipson & Posner, 2008; Charness & Gneezy, 2009), under-saving (Loewenstein et al., 2003) and suboptimal contracting (DellaVigna & Malmendier, 2004, 2006). Bénabou & Tirole (2004) model self-control problem as a form of "weakness of will". That

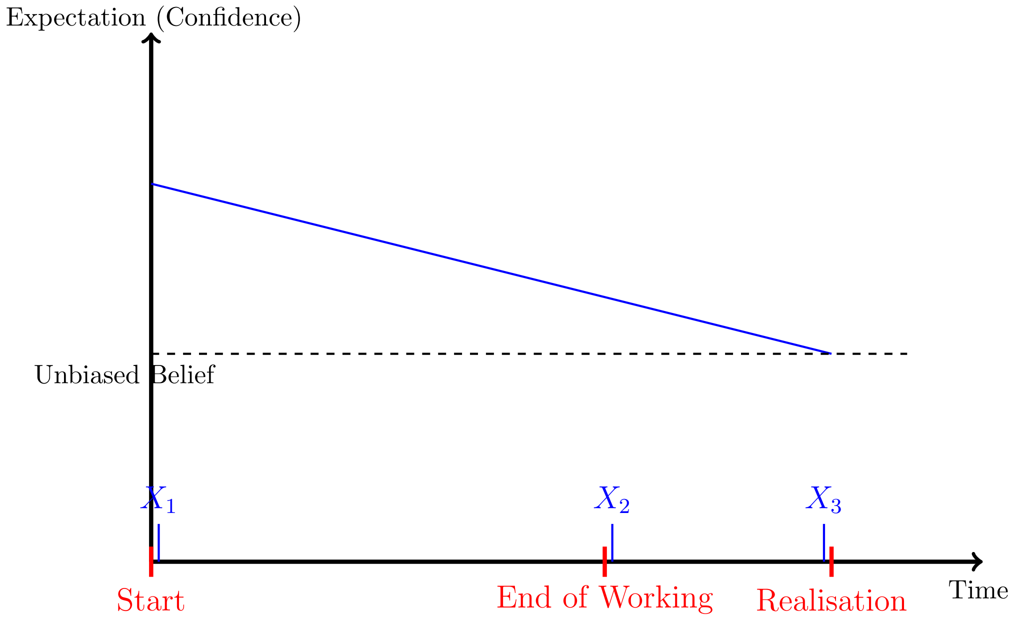

Figure 4.1: Dynamic overconfidence with the consumption motive

is, the agent has imperfect willpower, and any costly actions at present is subject to a temptation problem. Mathematically, an agent with the weakness of will is equivalent to an agent with hyperbolic discounting preference (Bénabou, 2015). In the present paper, I follow the classical hyperbolic discounting approach to model the self-control problem. Let $\beta \in (0, 1]$ be the hyperbolic discounting rate, which measures the degree of present bias (or her self-control ability), where $\beta = 1$ means the agent does not suffer from present bias and has perfect self-control ability. The following equation takes the self-control problem into consideration, and the solution predicts less effort exerted compared to the benchmark model.

$$\arg\max_{e} \quad U_1^T = -ce + \beta\omega_2\delta U_2^T + \beta\omega_3\delta^2 U_3^T \tag{4.10}$$

In addition, similar to the benchmark model, the agent anticipates that:

$$U_2^T = \omega_3 \delta U_3^T \tag{4.11}$$

$$U_3^T = \theta \ln(e) \tag{4.12}$$

Let e^{weak} be the equilibrium level of effort for the agent with the weakness of will:

$$e^{weak} = \frac{\beta\theta\delta^2\omega_3(1+\omega_2)}{c} \tag{4.13}$$

Compared with the benchmark case, it is straightforward to observe that due to self-control problem, the agent exerts less effort as $e^{weak} = \beta e^B$. The degree of shirking depends on her self-control ability β, the agent with less self-control ability shirks more. Shirking due to present bias is a welfare loss.[8] Therefore, in order to keep motivating oneself to exert enough efforts towards the optimal level, one should be overconfident, specifically, to hold an inflated belief about her ability θ.[9] Such cognitive distortions are denoted as *instrumental motive* (also known as *self-efficacy* motive in Bénabou & Tirole (2004) or *functional* motive in Bénabou & Tirole (2016)). In this model, I focus on the case that agent distorts her ability belief towards the ex-post optimal level of effort (which is e^B). In other words, the commitment device of being overconfident solves the self-control problem perfectly.

Instrumental Motive

Instrumental motive suggests that the agent distorts her ability for motivation, and I assume ability distortion is costly as well. Costs associated with ability distortion can be modelled with the same fashion (quadratic cost function) as payoff distortion, while in this section I assume the ability distortion cost $\psi > 0$ is fixed. The fixed cost assumption about ability distortion simplifies the analysis.[10] Assuming the agent is sophisticated that she knows her self-control ability β. Therefore she can deal with the self-control problem by inflating her belief about her own ability. Such ability distortion incurs a physical/mental cost ψ. As a consequence, the agent only boosts her perception about her ability if the benefit from exerting the ex-post optimal effort outweighs the cost of distortion. Let $I \in \{0, 1\}$ be the indicator of ability distortion. $I = 1$ if the agent chooses to inflate her belief about ability and $I = 0$ if not. θ^I is the distorted belief about the ability which leads to the ex-post optimal level of effort exertion. Then the agent solves the following equation in the face of the self-control problem and the

[8]In this paper, the welfare analysis follows the "long-run perspective" proposed by O'Donoghue & Rabin (1999). That is, the dis-utility due to present bias ("weakness of will") is excluded in the welfare calculation, and mathematically, $\beta = 1$ is used to identify the optimal strategies. Therefore, e^B is the optimal strategy and e^{weak} is suboptimal.

[9]The exact direction of belief distortion depends on the nature of the task: instrumental motive inflates belief when θ and e are complements, $V_{\theta e} > 0$. On the other hand, for tasks where θ and e are substitutes, agents may hold under-confident beliefs–a form of "defensive pessimism"(Bénabou & Tirole, 2002). Defensive pessimism often applies to tasks to achieve some threshold level of performance (e.g. Pass/Fail marking scheme)(Bénabou, 2015). In this paper, I model efforts and ability as complements.

[10]In Appendix C, I provide an alternative model where ability distortion cost is quadratic, and indeed the main implication is not qualitatively different from fixed cost model.

commitment device:

$$\begin{cases} \underset{\{I,e\}}{\arg\max} \quad U_1^T = -ce + \beta\omega_2\delta U_2^T + \beta\omega_3\delta^2 U_3^T - I\psi \\ \\ U_2^T = \omega_3\delta U_3^T \\ \\ U_3^T = I(\theta^I - \theta)\ln(e) + \theta\ln(e) \end{cases} \tag{4.14}$$

The equilibrium depends on the cost of ability distortion ψ. In this paper I focus on the most interesting case when $\psi \leq \bar{\psi}$ (the ability distortion cost is not too high[11]). And thus the solution of equation (4.14), $\{I^I, e^I\}$ (superscript I stands for "instrumental"), is:

$$\begin{cases} I^I = 1 \\ \\ e^I = \dfrac{\theta\delta^2\omega_3(1+\omega_2)}{c} \end{cases} \tag{4.15}$$

The above result indicates that when the distortion cost is not too high, the agent chooses to inflate her belief on her own ability to motivate herself. In equilibrium, her belief about her ability is higher than her true ability as $\theta^I = \frac{\theta}{\beta}$. By taking this commitment device, she is able to exert the optimal level of effort in the face of the self-control problem as $e^I = e^B > e^{weak}$. In addition, her payoff expectation is also distorted because of the inflation of ability:

$$X_1^I = \frac{\theta}{\beta}\ln\big(e^I\big) > \theta\ln\big(e^I\big) \tag{4.16}$$

Therefore, the instrumental motive causes overconfidence ($X_1^I > \theta\ln\big(e^I\big)$) and the degree of overconfidence depends on the agent's self-control ability, β. The agent with low self-control ability holds more overconfident beliefs because she faces greater temptation and requires higher inflation of ability for motivation. And higher inflation of ability leads to higher payoff expectation.

For $t = 2$ and $t = 3$, the agent is no longer able to exert additional effort and thus the self-control problem does not matter. Therefore the agent does not distort her ability because it is costly and useless to do so (since the effort is already

[11]The threshold value $\bar{\psi}$ is positive and negatively determined by β . When $\psi > \bar{\psi}$, no ability distortion adopted since it is too costly. Details can be found in Appendix C

exerted at $t = 1$). That is:

$$\begin{cases} X_2^I = \theta \ln\left(e^I\right) \\ \\ X_3^I = \theta \ln\left(e^I\right) \end{cases} \tag{4.17}$$

Summary 2. Instrumental motive leads to the emergence of overconfident beliefs while the agent is working. The sophisticated agent who faces the self-control problem has an incentive to inflate her belief about her own ability for motivation to resist the present temptation. Her payoff expectation is inevitably inflated while she chooses to bias the perception about her ability upwardly. Instrumental motive is gone after the working period and thus the agent's beliefs become unbiased afterwards.

Figure 4.2 shows the dynamic of overconfidence with the instrumental motive.

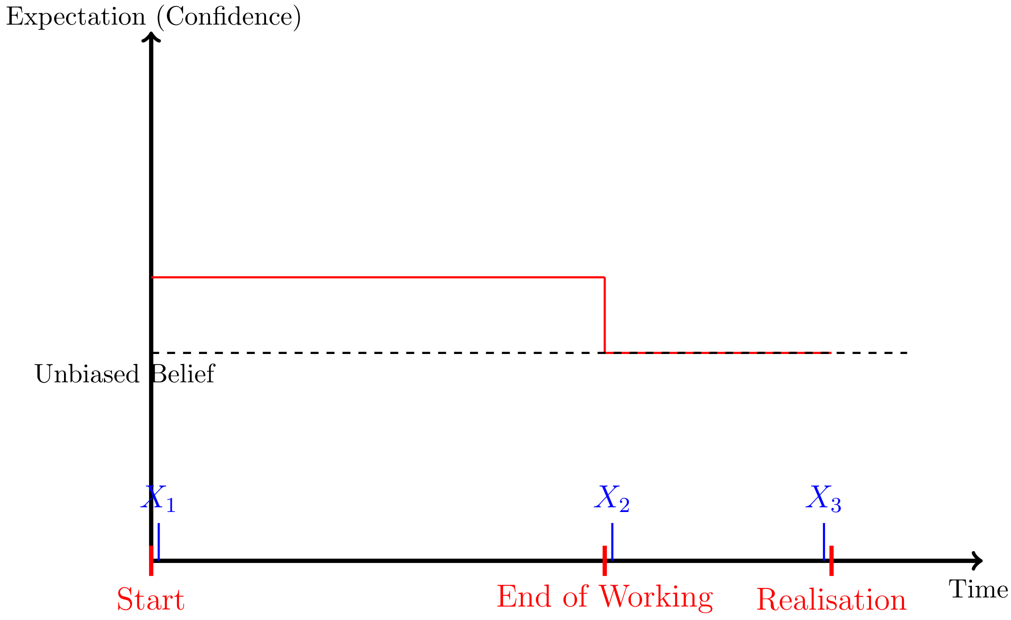

Figure 4.2: Dynamic overconfidence with instrumental motive only

4.3.4 A Nested Model

In this section, I nest consumption and instrumental motives into the benchmark model. This is done because both consumption and instrumental motives may affect the agent's belief simultaneously and interdependently. At $t = 1$, the agent chooses her belief in her ability $\theta^I = \frac{\theta}{\beta}$ for instrumental purpose. The subscript $|_{\theta^I}$ stands for the fact that the agent believes that her ability is θ^I at that time. Then, she inflates her belief in the payoff for savouring. The ability distortion cost $\psi < \bar{\psi}$ is fixed and the payoff distortion cost, $\lambda(X_1 - \theta^I \ln e)^2$, is quadratic. The intrapersonal equilibrium of the nested model, $\{e^N, X_1^N, X_2^N, X_3^N\}$, is derived from the following equations:

$$\underset{\{e,\ X_1\}}{\arg\max} \quad U_1^T|_{\theta^I} = -ce + \beta\omega_2\delta U_2^T + \beta\omega_3\delta^2 U_3^T + s\tau_1 X_1 - \lambda(X_1 - \theta^I \ln e)^2 - \psi \quad (4.18)$$

At $t = 1$, the agent anticipates that the optimal level of belief to hold are $X_2^N|_{\theta^I}$ and $X_3^N|_{\theta^I}$ that:

$$\underset{X_2}{\arg\max} \quad U_2^T|_{\theta^I} = \omega_3\delta U_3^T|_{\theta^I} + s\tau_2 X_2 - \lambda(X_2 - \theta^I \ln(e))^2 \quad (4.19)$$

$$\underset{X_3}{\arg\max} \quad U_3^T|_{\theta^I} = \theta^I \ln(e) - \lambda(X_3 - \theta^I \ln(e))^2 \quad (4.20)$$

The solution is:

$$\begin{cases} e^N = \dfrac{s\tau_1\theta}{\beta c} + \dfrac{\delta\theta(s\tau_2\omega_2 + \delta\omega_3(1+\omega_2))}{c} \\[2ex] X_1^N|_{\theta^I} = \dfrac{s\tau_1}{2\lambda} + \dfrac{\theta}{\beta}\ln\big(e^N\big) \\[2ex] X_2^N|_{\theta^I} = \dfrac{s\tau_2}{2\lambda} + \dfrac{\theta}{\beta}\ln\big(e^N\big) \\[2ex] X_3^N|_{\theta^I} = \dfrac{\theta}{\beta}\ln\big(e^N\big) \end{cases} \quad (4.21)$$

The main implications are summarised in the following section. Importantly, $X_2^N|_{\theta^I}$ and $X_3^N|_{\theta^I}$ derived from the above equations are based on her belief that her ability is θ^I at $t = 1$ and not equal to the actual equilibrium beliefs at $t = 2$ and $t = 3$. The actual equilibrium level of beliefs are derived at $t = 2$ and $t = 3$ where her belief about her ability is unbiased θ.

At $t = 2$, the agent has finished working and thus the instrumental motive no longer presents. In other words, the agent is not incentivised to inflate her belief about her ability to deal with the self-control problem. Therefore, she holds an unbiased belief about θ. On the other hand, as she still savours the upcoming payoff, consumption motive continues to affect her belief about the payoff.

$$\underset{X_2}{\arg\max} \quad U_2^T|_{\theta} = \omega_3\delta U_3^T|_{\theta} + s\tau_2 X_2 - \lambda(X_2 - \theta \ln\big(e^N\big))^2 \quad (4.22)$$

At $t = 3$, the agent has no time for savouring as $\tau_3 = 0$ and no need to deal with temptation as the effort is already exerted. Therefore, consistent with all previous models, the agent's confidence converges to the unbiased level as:

$$\underset{X_3}{\arg\max} \quad U_3^T|_\theta = \theta \ln\left(e^N\right) - \lambda(X_3 - \theta \ln\left(e^N\right))^2 \tag{4.23}$$

Solving equation (4.22) and (4.23) to get:

$$\begin{cases} X_2^N|_\theta = \dfrac{s\tau_2}{2\lambda} + \theta \ln\left(e^N\right) \\ \\ X_3^N|_\theta = \theta \ln\left(e^N\right) \end{cases} \tag{4.24}$$

The above solution represents the actual equilibrium level of belief. Importantly, the equilibrium result differs from $X_2^N|_{\theta^I}$ and $X_3^N|_{\theta^I}$ because the later two are based on the belief that the agent's ability is θ^I, however, when the agent enters the waiting period, the perception about her ability becomes unbiased θ as instrumental motive no longer presents. Therefore, the intrapersonal equilibrium of the nested model is:[12]

$$\begin{cases} e^N = \dfrac{s\tau_1}{\beta c} + \dfrac{\delta\theta(s\tau_2\omega_2 + \delta\omega_3(1+\omega_2))}{c} \\ \\ X_1^N = \dfrac{s\tau_1}{2\lambda} + \dfrac{\theta}{\beta} \ln\left(e^N\right) \\ \\ X_2^N = \dfrac{s\tau_2}{2\lambda} + \theta \ln\left(e^N\right) \\ \\ X_3^N = \theta \ln\left(e^N\right) \end{cases} \tag{4.25}$$

4.3.5 Implications

In this section, I analysis the main implications of the nested model. First, overconfident beliefs arise in equilibrium due to consumption and instrumental motives. Second, overconfident beliefs diminish over time and a substantial decrease is expected after the working period. Third, the equilibrium level of effort is boosted by these two motives. Finally, compared to the single motive models, the nested model shows that the interplay of these two motives further increases the equilibrium level of effort and the degree of overconfidence.

[12] The proof is similar to that for the consumption motive equilibrium presented in Appendix B.

The Emergence and Motivation of Overconfidence

First, overconfidence is predicted by the present model even if belief distortion is costly. Let D_t^N, the magnitude of belief bias (overconfidence), represents the difference between the equilibrium level of payoff belief and the unbiased payoff expectation at t:

$$D_t^N = X_t^N - \theta \ln\left(e^N\right) \tag{4.26}$$

Therefore $D_1^N = \frac{s\tau_1}{2\lambda} + \frac{(1-\beta)\theta}{\beta} \ln\left(e^N\right) > 0$, $D_2^N = \frac{s\tau_2}{2\lambda} > 0$ and $D_3^N = 0$. And thus the agent holds overconfident beliefs at both $t = 1$ and $t = 2$. The overconfidence diminishes over time and the agent eventually holds an unbiased belief ($D_3^N = 0$).

In addition to the emergence of overconfidence, this model shows that both consumption motive and instrumental motive lead to overconfident belief on payoff at $t = 1$ and only consumption motive at $t = 2$.

$$\begin{aligned} D_1^N &= \underbrace{\frac{s\tau_1}{2\lambda}}_{consumption} + \underbrace{\frac{1-\beta}{\beta}}_{instrumental} \theta \ln\left(e^N\right) \\ D_2^N &= \underbrace{\frac{s\tau_2}{2\lambda}}_{consumption} < D_1^N \\ D_3^N &= 0 \end{aligned} \tag{4.27}$$

Equation (4.27) has intuitive interpretation. First, the consumption motive is positively driven by the net anticipatory parameter s since when savouring is more important, agent chooses to bias her belief upwards more. On the other hand, the consumption motive is negatively affected by λ: agent who is more realism holds less overconfident belief in equilibrium as it is more costly to inflate their beliefs. Second, the instrumental motive is negatively correlated with one's self-control ability β. Agent who suffers more from self-control problem holds more overconfident belief because they require a stronger incentive to deal with the temptation. Figure 4.3 presents the timing of these two motives.

The Dynamic of Overconfidence

The dynamic effect of the two motives leads to the dynamic of overconfidence in equilibrium. The following equations show that the agent's confidence level is

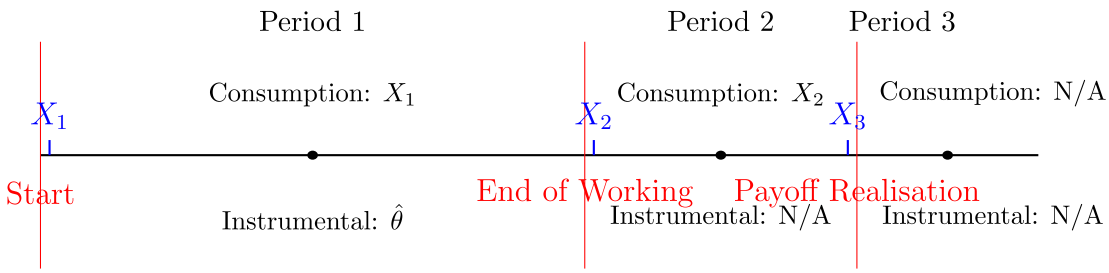

Figure 4.3: Timeline of the nested model

shifting over time.

$$\begin{aligned} D_1^N - D_2^N &= \underbrace{\frac{s\tau_1 - s\tau_2}{2\lambda}}_{\Delta consumption>0} + \underbrace{\frac{(1-\beta)}{\beta}}_{\Delta instrumental>0} \theta \ln\left(e^N\right) > 0 \\ D_2^N - D_3^N = D_2^N &= \underbrace{\frac{s\tau_2}{2\lambda}}_{\Delta consumption} > 0 \end{aligned} \tag{4.28}$$

Equation (4.28) indicates that overconfidence diminishes over time. Figure 4.4 graphically shows the diminishing confidence level. The full line stands for the confidence of the agent across time. The red vertical line represents the substantial decrease in confidence after working as the instrumental motive disappears. The dashed line is the unbiased level of confidence, and thus the area above indicates overconfidence.

The Boost of Effort

Both consumption and instrumental motives increase the equilibrium level of effort. When the agent cares about the anticipatory utility, she chooses to work more to savour the positive consequence of working. In addition, the agent manages to deal with the self-control problem by believing that her effort provides greater rewards. The magnitude of the boost is shown by:

$$e^N - e^{weak} = \frac{s\tau_1\theta}{\beta c} + \frac{\delta\theta s\tau_2\omega_2}{c} + \frac{(1-\beta)\theta\delta^2\omega_3(1+\omega_2)}{c} \tag{4.29}$$

The degree of effort increase depends negatively on the agent's self-control ability β as $\frac{\partial(e^N - e^{weak})}{\partial\beta} < 0$. It is because the instrumental motive is of less importance to the agent with greater self-control ability. In addition, the consumption motive boosts the effort more for the agent with greater savouring parameter s as

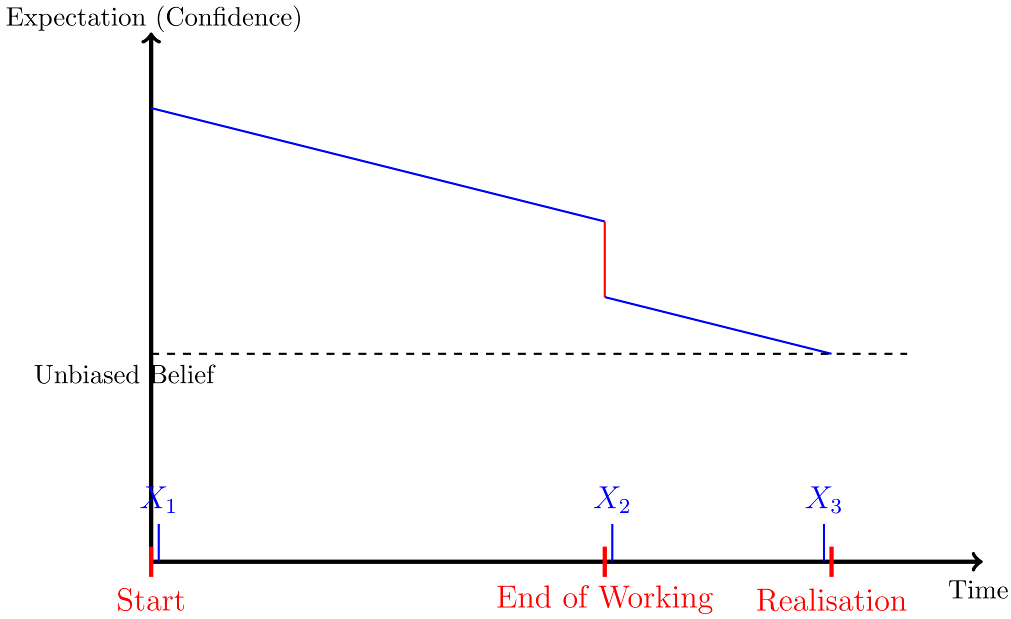

Figure 4.4: Dynamic overconfidence with consumption and instrumental motives

$\frac{\partial(e^N - e^{weak})}{\partial s} > 0$, because the agent who cares more about the anticipatory feelings chooses to work more to savour the positive expectation.

The Interplay of Two Motives

Overconfidence caused by these two motives can be disentangled theoretically; however, the interaction of these two motives further boosts the agent's effort and overconfidence. In a single motive model, the increases of effort are:

$$\begin{cases} e^C - e^B = \dfrac{s\theta(\tau_1 + \delta\tau_2\omega_2)}{c} \\ e^I - e^{weak} = \dfrac{(1-\beta)\theta\delta^2\omega_3(1+\omega_2)}{c} \end{cases} \tag{4.30}$$

The effort increase of the nested model as shown in equation (4.29) can be rewritten as:

$$e^N - e^{weak} = (e^C - e^B) + (e^I - e^{weak}) + \frac{(1-\beta)s\theta\tau_1}{\beta c} \tag{4.31}$$

Therefore, compared with the single motive models, the equilibrium level of effort in the nested model is further boosted by $\frac{(1-\beta)s\theta\tau_1}{\beta c}$, which is negatively correlated with self-control ability β and positively correlated with the savouring parameter s. The basic idea behind the interplay is, as the agent believes her ability is higher due to the instrumental motive, the payoff distortion becomes less costly compared to the case of no ability distortion. Therefore, the agent is motivated to hold an even higher belief on the payoff, for which additional effort has to be exerted in the equilibrium. In another word, the marginal cost of exerting effort always equals the net marginal benefit of holding an inflated belief[13]. When the net marginal benefit increases due to the instrumental motive, the equilibrium effort also rises. Consequently, the degree of overconfidence is inflated by the interplay since the effort is higher. This is shown in the following table.

	Benchmark	**Consumption**	**Instrumental**	**Nested (both)**
D_1	0	$\frac{s\tau_1}{2\lambda}$	$\frac{1-\beta}{\beta}\theta\ln\left(e^I\right)$	$\frac{s\tau_1}{2\lambda}+\frac{1-\beta}{\beta}\theta\ln\left(e^N\right)$
D_2	0	$\frac{s\tau_2}{2\lambda}$	0	$\frac{s\tau_2}{2\lambda}$
D_3	0	0	0	0

Table 4.1: The degree of overconfidence

Table 4.1 summarises the degree of overconfidence of different models at each period. The first row of the table shows that the interplay of these two motives promotes the overconfident belief further as $D_1^C + D_1^I < D_1^N$. This is because the effectiveness of the instrumental motive depends on the equilibrium level of effort, which is further inflated by the interplay of the two motives.

Summary 3. Both consumption and instrumental motive lead to the emergence of overconfident beliefs while she is working. At the same time, the agent works more. After the working period, only consumption motive presents and keeps motivating overconfident beliefs until the end of the waiting period. As a result, the agent is most overconfident at the beginning of the working period and her confidence level diminishes over time. Then a substantial decrease in confidence occurs after the working period, after which her expectation continues to diminish during the waiting period. In the end, her belief becomes unbiased. Also, compared with the single motive models, the interplay of these two motives further promotes effort and overconfidence.

4.4 Conclusion

The consumption and instrumental motives are proposed by economists to explain the prevalence of overconfidence. This chapter develops a simple theoretical framework to model the dynamic of overconfidence. I argue that the dynamic of overconfidence is predictable and is not necessarily caused by learning. Instead, the degree of overconfidence depends on the waiting time until final payoff and

[13]The net marginal benefit of inflated belief is the marginal benefit from savouring minus the distortion cost.

the stage of working. For the consumption motive, the agent inflates her expectation more when there are more time and opportunities for savouring. For the instrumental motive, the agent with self-control problem holds overconfident beliefs while working. The dynamic overconfidence prediction is based on two distinctive features of this model. First, I introduce a quadratic cost function for belief distortion, which ensures that extreme beliefs are rare. Second, my model includes an additional waiting stage which is very common in practice but largely ignored by the literature. My model suggests that studies on overconfidence should consider the fact that an individual potentially derives anticipatory utility during the waiting stage.

The consumption and instrumental overconfidence suggest that overconfidence is a form of self-deception. Individuals are self-deceptive towards inflated self-judgement consciously or unconsciously. Three main types of tools are adopted by individuals to achieve self-deceptive overconfidence: strategic ignorance, reality denial and self-signalling (see, Bénabou & Tirole, 2016). However, empirical evidence is limited in the existing literature. In Chapter 5, I provide some empirical results on the intrapersonal overconfidence in the field of education.

Appendices

A Proof of Benchmark Model Equilibrium

Anticipating that $U_2^T = \omega_3 \delta U_3^T$ and $U_3^T = \theta \ln(e)$, the agent faces a optimisation problem of:

$$\arg\max_{e} \quad U_1^T = -ce + \omega_2 \delta \omega_3 \delta \theta \ln(e) + \omega_3 \delta^2 \theta \ln(e) \tag{32}$$

Then take partial derivatives with respect to e to get:

$$\frac{\partial U_1^T}{\partial e} = \frac{\delta^2 \omega_3 (1+\omega_2)\theta}{e} - c$$

$$\frac{\partial^2 U_1^T}{\partial e^2} = \frac{-\delta^2 \omega_3 \theta (1+\omega_2)}{e^2} < 0$$

Let the first order derivative equal zero to get $e^B = \frac{\theta \delta^2 \omega_3 (1+\omega_2)}{c}$ and it is a local maximum. In addition, given the constraint $e \in (0, \infty)$ is linear, the feasible region is convex. Given the objective function is convex, the solution above is a global maximum.

B Proof of Consumption Motive Equilibrium

To solve equation (4.6), (4.7) and (4.8), I first show that from equation (4.8), $X_3^C = \theta \ln(e)$. That is, the optimal expectation to hold for the agent at $t = 3$, is the unbiased belief. This result is intuitive since when there is no savouring utility, there is no incentive for belief distortion.

Then we substitute $X_3^C = \theta \ln(e)$ into equation (4.7) to get:

$$\arg\max_{X_2} \quad U_2^T = \omega_3 \delta \theta \ln(e) + s\tau_2 X_2 - \lambda (X_2 - \theta \ln(e))^2 \tag{33}$$

Then take partial derivatives with respect to X_2 to get:

$$\frac{\partial U_2^T}{\partial X_2} = s\tau_2 - 2\lambda X_2 + 2\lambda \theta \ln(e)$$

$$\frac{\partial^2 U_2^T}{\partial X_2^2} = -2\lambda < 0$$

Therefore, the optimal level of expectation to hold, X_2^C, is:

$$X_2^C = \frac{s\tau_2}{2\lambda} + \theta \ln(e) \tag{34}$$

Equation 34 shows that the optimal expectation to hold at $t = 2$ is a best response function to the effort exerted. Therefore, we are able to substitute equation 34 and $X_3^C = \theta \ln(e)$ into equation (4.6):

$$\begin{aligned} \underset{\{e,\ X_1\}}{\arg\max} \quad U_1^T = -ce + \omega_2\delta\big[\omega_3\delta\theta\ln(e) + s\tau_2(\frac{s\tau_2 + 2\lambda\theta\ln(e)}{2\lambda}) - \lambda(\frac{s\tau_2}{2\lambda})^2\big] \\ + \omega_3\delta^2\big[\delta\theta\ln(e)\big] + s\tau_1 X_1 - \lambda(X_1 - \theta\ln(e))^2 \end{aligned} \tag{35}$$

Let the following first order conditions (FOCs) equal zero.

$$\frac{\partial U_1^T}{\partial e} = \frac{-ce + \theta(\delta s\tau_2\omega_2 + \delta^2\omega_3(1+\omega_2) + 2\lambda X_1) - 2\theta^2\lambda\ln(e)}{e} = 0$$

$$\frac{\partial U_1^T}{\partial X_1} = s\tau_1 - 2\lambda X_1 + 2\lambda\theta\ln(e) = 0$$

Solving the above two equations to get the critical point:

$$\begin{cases} e^C = \dfrac{s\theta(\tau_1 + \delta\tau_2\omega_2) + \theta\delta^2\omega_3(1+\omega_2)}{c} \\ X_1^C = \dfrac{s\tau_1}{2\lambda} + \theta\ln\left(\dfrac{s\theta(\tau_1 + \delta\tau_2\omega_2) + \theta\delta^2\omega_3(1+\omega_2)}{c}\right) \end{cases} \tag{36}$$

To test this point, use the second-order partial derivatives:

$$\frac{\partial^2 U_1^T}{\partial (e^C)^2} = \frac{-\theta\delta^2\omega_3(1+\omega_2)}{(e^C)^2} < 0$$

$$\frac{\partial^2 U_1^T}{\partial (X_1^C)^2} = -2\lambda < 0$$

$$\frac{\partial U_1^T}{\partial e^C \partial X_1^C} = \frac{2\lambda\theta}{e^C} > 0$$

Consequently we have:

$$\frac{\partial^2 U_1^T}{\partial (e^C)^2}\cdot\frac{\partial^2 U_1^T}{\partial (X_1^C)^2}-\big(\frac{\partial U_1^T}{\partial e^C \partial X_1^C}\big)^2=\frac{2\lambda\theta(\delta s\tau_2\omega_2+\delta^2\omega_3(1+\omega_2)+s\tau_1)}{e^2}>0$$

Therefore, the unique critical point identified is a local maximum.

In addition, since $\frac{\partial U_1^T}{\partial X_1}=s\tau_1-2\lambda(X_1-\theta\ln(e))$, underconfidence nor the unbiased belief, $X_1\leq\theta\ln(e)$, is never optimal over the domain. Thus we can only focus on the feasible sets where $X_1>\theta\ln(e)$. Let $det(H_i)$ be the determinants of ith principal minor of the following Hessian matrix $Hess(U_1^T)$. Thus $det(H_2)=\frac{\partial^2 U_1^T}{\partial e^2}\cdot\frac{\partial^2 U_1^T}{\partial X_1^2}-[\frac{\partial U_1^T}{\partial e\partial X_1}]^2$, simplify to get:

$$det(H_2)=\frac{2\lambda\theta[\delta s\tau_2\omega_2+\delta^2\omega_3(1+\omega_2)+2\lambda(X_1-\theta\ln(e))]}{e^2}>0$$

In addition,

$$\frac{\partial^2 U_1^T}{\partial X_1^2}=-2\lambda<0$$

The Hessian matrix of U_1^T is:

$$Hess\left(U_1^T\right)=\begin{bmatrix}\frac{-\theta\delta^2\omega_3(1+\omega_2)}{(e^C)^2} & \frac{2\lambda\theta}{e}\\ \\ \frac{2\lambda\theta}{e} & -2\lambda\end{bmatrix}\tag{37}$$

The Hessian matrix is negative definite as $det(H_1)=\frac{-\theta\delta^2\omega_3(1+\omega_2)}{(e^C)^2}<0$ and $det(H_2)=\frac{2\lambda\theta[\delta s\tau_2\omega_2+\delta^2\omega_3(1+\omega_2)+2\lambda(X_1-\theta\ln(e))]}{e^2}>0$. Therefore, U_1^T is strictly concave over the domain $\{X_1>0,e>0,X_1>\theta\ln(e)\}$ and thus $\{e^C,\ X_1^C\}$ is a global maximum over such domain.

C Proof of Instrumental Motive Equilibrium

Fixed ability distortion cost and the threshold $\bar{\psi}$

In the face of the self-control problem, the agent decides whether or not to inflate the belief about her own ability, given the belief distortion cost is ψ. To find the solution, I first look at the case the agent does not adopt ability distortion due to distortion cost (ψ is large), $I=0$. If $I=0$, the effort exerted is e^{weak}. The welfare[14] given no ability distortion is:

$$W|_{I=0} = -ce^{weak} + \omega_2\omega_3\delta\theta \ln\left(e^{weak}\right) + \omega_3\delta^2\theta \ln\left(e^{weak}\right) \tag{38}$$

On the other hand, an agent may adopt ability distortion when the distortion cost is reasonably low. For $I = 1$ her belief about her ability is θ^I and the utility is thus:

$$W|_{I=1} = -ce^B + \omega_2\omega_3\delta\theta \ln\left(e^B\right) + \omega_3\delta^2\theta \ln\left(e^B\right) - \psi \tag{39}$$

Therefore, the agent chooses to inflate her belief about her own ability if and only if $W|_{I=1} - W|_{I=0} \geq 0$[15].

$$W|_{I=1} - W|_{I=0} = (\beta - 1 - \ln(\beta))\delta^2\omega_3\theta(1+\omega_2) - \psi \tag{40}$$

Given $0 < \beta < 1$, $\beta - 1 - \ln(\beta) > 0$. Therefore, a positive threshold value, $\bar{\psi} = (\beta - 1 - \ln(\beta))\delta^2\omega_3\theta(1+\omega_2)$, is identified. The agent will choose to inflate her ability for motivation if and only if $\psi \leq \bar{\psi}$. In addition, since $\frac{\partial\bar{\psi}}{\partial\beta} = 1 - \frac{1}{\beta} < 0$, the threshold value is negatively correlated with the agent's self-control ability. This result is intuitive in the sense that the agent with greater self-control ability has less incentive to take a commitment device.

Quadratic ability distortion cost

In the previous part, I identify the threshold value of the fixed ability distortion cost. In this part, I show that when the ability distortion cost is variable and quadratic, the main message of the model does not change.

The ability distortion can be modeled in the same way as the payoff distortion. The cost depends on the degree of distortion and the level of realism of the agent. Let $C(\hat{\theta})$ be such cost, $\hat{\theta}$ be the distorted ability, then:

$$C(\hat{\theta}) = \lambda(\hat{\theta} - \theta)^2 \tag{41}$$

On the other hand, the benefit of ability distortion is through the lens of effort

[14] As mentioned in the main text, the welfare calculation does not take present bias into consideration. Also, as it is ex-post utility, any distortions e.g. $\hat{\theta}$ do not affect the welfare directly. I define U_1 with $\beta = 1$ as the agent's ex-post total welfare. The reason U_1 represents the total welfare level is because the definition of U_1 has already takes the subsequent u_2 and U_3 into consideration through the weighting parameter ω_2 and ω_3.

[15] Clearly the conduct of the commitment device (ability distortion) requires some level of self-control ability. In the paper I assume the agent is able to successfully commit if it is beneficial.

boost, which increases the ex-post welfare for the agent with self-control problem. Let $B(\hat{\theta})$ represent the benefit of ability distortion, which is the difference between the ex-post welfare $W_{\hat{\theta}} - W_{\theta}$.

$$
\begin{aligned}
B(\hat{\theta}) &= W_{\hat{\theta}} - W_{\theta} \\
W_{\hat{\theta}} &= -ce^{\hat{\theta}} + \omega_2\omega_3\delta\theta \ln\left(e^{\hat{\theta}}\right) + \omega_3\delta^2\theta \ln\left(e^{\hat{\theta}}\right) - \lambda(\hat{\theta} - \theta)^2 \\
W_{\theta} &= -ce^{weak} + \omega_2\omega_3\delta\theta \ln\left(e^{weak}\right) + \omega_3\delta^2\theta \ln\left(e^{weak}\right)
\end{aligned}
\tag{42}
$$

Therefore the agent chooses the degree of distortion $\hat{\theta} - \theta$ to maximise the net benefit, $B(\hat{\theta}) - C(\hat{\theta})$. We take a look at the marginal benefit and marginal cost of ability distortion.

$$
MC = \frac{\partial C(\hat{\theta})}{\partial \hat{\theta}} = 2\lambda(\hat{\theta} - \theta) > 0 \tag{43}
$$

The marginal cost is straightforward to get and it is positive and increasing with the degree of the distortion. The marginal benefit is the marginal increase in the welfare and it can be decomposed into two parts:

$$
\begin{aligned}
MB = \frac{\partial B(\hat{\theta})}{\partial \hat{\theta}} &= \frac{\partial e^{\hat{\theta}}}{\partial \hat{\theta}} \cdot \frac{\partial W_{\hat{\theta}}}{\partial e^{\hat{\theta}}} \\
&= \frac{\delta^2\omega_3(1+\omega_2)}{c} \cdot \left[\frac{\omega_3\delta\theta(\omega_2+\delta)}{e} - c\right] \\
&= \frac{\delta^3\omega_3^2\theta(1+\omega_2)(\omega_2+\delta)}{ce} - \delta^2\omega_3(1+\omega_2) \\
&= \frac{\delta^2\omega_3(1+\omega_2)\left[\delta\omega_3\theta(\omega_2+\delta) - ce\right]}{ce}
\end{aligned}
\tag{44}
$$

First, the above equation shows $\frac{\partial e^{\hat{\theta}}}{\partial \hat{\theta}} > 0$, that is, the equilibrium level of effort is positively correlated with the magnitude of belief inflation. The more competent the agent believes she is, the more effort she should exert in terms of the ex-post welfare. Second, the marginal benefit diminishes as e increases, since:

$$
\begin{aligned}
\frac{\partial MB}{\partial e} &= \delta^3\omega_3^2\theta(1+\omega_2)(\omega_2+\delta)(\frac{1}{c} - 2e) \\
\frac{\partial MB^2}{\partial^2 e} &= -2\delta^3\omega_3^2\theta(1+\omega_2)(\omega_2+\delta) < 0
\end{aligned}
\tag{45}
$$

Therefore, we can conclude that the marginal benefit is diminishing with the degree of ability distortion $\hat{\theta}-\theta$. So the problem is a standard increasing marginal cost and decreasing marginal return problem. The solution is reached by setting $MB = MC$.

$$MB = MC$$

$$\frac{\delta^2\omega_3(1+\omega_2)\left[\delta\omega_3\theta(\omega_2+\delta) - ce^{\hat{\theta}}\right]}{ce^{\hat{\theta}}} = 2\lambda(\hat{\theta}-\theta) \tag{46}$$

$$\hat{\theta} = \theta + \frac{\delta^2\omega_3(1+\omega_2)\left[\delta\omega_3\theta(\omega_2+\delta) - ce^{\hat{\theta}}\right]}{2\lambda ce^{\hat{\theta}}}$$

Substitute $e^{\hat{\theta}} = \frac{\hat{\theta}\delta^2\omega_3(1+\omega_2)}{c}$ into the above equation:

$$\hat{\theta} = \theta + \frac{\sqrt{8(1-\delta)\delta\lambda\omega_2\omega_3\theta + [\delta^2\omega_3(1+\omega_2)+2\lambda\theta]^2} - \delta^2\omega_3(1+\omega_2) - 2\lambda\theta}{4\lambda} \tag{47}$$

As $8(1-\delta)\delta\lambda\omega_2\omega_3\theta > 0$, $\hat{\theta} > \theta$. Thus my model also predicts the emergence of overconfidence with a quadratic ability distortion cost.

CHAPTER 5 MOTIVATED OVERCONFIDENCE: AN ONLINE FIELD STUDY

5.1 Introduction

In Chapter 4, I develop a simple theoretical model on motivated overconfidence. The main aim of this chapter is to provide an empirical test on the validity of the proposed consumption and instrumental motives behind overconfidence. While the idea of motivated overconfidence appears to be theoretically convincing, I am not aware of any empirical studies verifying the existence of these two motives. The lack of experimental evidence is likely to be caused by the challenging nature of the problem. Empirical research (e.g. traditional laboratory experiments) on motivated overconfidence is difficult to conduct for a number of reasons. First, it is often demanding to separate the effect of the consumption (savoury) motive and the instrumental motive. Both motives cause overconfidence but through fundamentally different channels. Just observing whether or to what extent one is overconfident does not help to identify the underlying motives. A successful study must be able to separate these two effects. Second, high stakes might be necessary to trigger cognitive distortions. An individual is likely to distort her belief to resist present temptation if the self-control problem is significantly costly. Similarly, for the consumption motive, small stakes (e.g. £20 rewards in a laboratory experiment) are unlikely to induce any significant savouring utility. Third, a long waiting period before the reward is required to study the savouring behaviour and the experimenter has to collect the individual's beliefs multiple times across time to observe the dynamics of overconfidence predicted in theory. Such design features (long delay of payment, subjects called to the lab multiple times) are often costly and impractical to implement in a lab.

With this chapter, I intend to contribute to the literature empirically and methodologically with a novel design of an online field study. A total of three online surveys are delivered to students completing a compulsory economics coursework to measure their grade expectation.[1] All three surveys ask students to self-report their current best prediction about their essay performance. The three surveys are delivered at the following periods: the first is when students start working on the essay, the second is when students have just submitted their work, and the third one is just before result realisation. This design overcomes the above difficulties. First, the timing of the surveys, together with the nature of the task,

[1]Detailed questions are available upon request.

help to separate the potential consumption and instrumental motives. Second, this study recruits highly motivated students from a leading research university in the UK. The compulsory coursework essay contributes to their final grade significantly, and thus subjects care about their essay performance. Third, we collect subjects' self-reported expectations through the online learning platform "Blackboard Learn", which is being used on a daily basis by the students. Therefore, the subjects can participate easily, and their responses are kept at a secure place in an anonymous way.

The data of this study suggests that students hold dynamic beliefs about their essay performance. Although absolute overconfidence is absent, students are most confident about their performance while working. Then after submission, students, especially those who have a greater degree of self-control problem, adjust their expectations downwards significantly. Then the confidence level stays unchanged until result realisation. The dynamics of the confidence level is consistent with a possibility that students adopt inflated beliefs as a motivator to pursue difficult goals, providing an experimental support for the instrumental motive of overconfidence. In contrast, the consumption motive hypothesis is not compatible with the data. Students do not hold higher expectations while waiting for result realisation.

5.2 Literature Review

In Chapter 4 of this thesis, I summarise the literature on motivated overconfidence theory, as well as general empirical evidence on the existence of overconfidence. In this section, I focus on the experimental evidence on student overconfidence.

In the economics of education literature, overconfidence is often studied through the lens of grade forecasts.[2] Numerous research studies have found that students, in general, are overconfident about their academic performance both relatively and absolutely. I begin with the most closely related one. Grimes (2002) finds that students' performance forecasts are subject to a pervasive degree of overconfidence. In his study, self-reported expectations about the exam performance

[2] Apart from grade forecasts, student overconfidence has been found from a number of other perspectives. Students hold overconfident beliefs on the insightfulness of their own judgments, examples including answering general knowledge questions (Fischhoff et al., 1977) and forecasting what events they will experience during the semester (Dunning et al., 1991). College students also tend to believe that they are above average in desirable abilities (Dunning et al., 2004). Also, students overestimate the probability that their own future decisions will be socially desirable, while their expectations regarding other students' pro-social behaviour are more accurate (Epley & Dunning, 2000, 2006).

are collected at three points in time: 48 hours before the exam, just before the exam and just after the exam. Students' forecasts are significantly higher than their actual performance for all three surveys. However, the performance expectation becomes much lower (yet still overconfident) for the post-exam survey.[3] Moreland & Sweeney (1984) conducted a survey-based study with undergraduate students and found that students have a strong general preference for positive rather performance evaluations regardless of their self-expectancies. They believe their result might be explained by the self-enhancement effects (e.g. Cohen, 1959; Brown et al., 1988) that people react favourably to positive performance evaluations to enhance their self-image.

Grimes et al. (2004) also find evidence for the existence of student overconfidence, as more than 70 percent of the students predict that their exam score higher than what they achieve. Serra & DeMarree (2016) collect students' reports on the desired level of performance and grade forecasts. Consistent overconfidence is identified and they argue that it is because students' predictions are biased towards their desired level of performance. Students also consistently overestimate how easily they can complete academic tasks, a phenomenon named "planning fallacy" (Buehler et al., 1994). For example, the amount of time undergraduate students spend to complete their thesis is three weeks longer than their self-reported most "realistic" estimation, and one week more than what they believe as the "worst case" scenario.

Also, heterogeneous patterns of student overconfidence have been identified by earlier studies. Specifically, male students tend to be more overconfident than female students, and weak students are more overconfident than strong students. Lundeberg et al. (1994) find that while both male and female students overestimate their academic performance, males are much more overconfident especially when their answers are wrong. Their finding is consistent with "the male answer syndrome", whereby men tend to have opinions even on subjects they do not have any ideas about (Campbell, 1992). In general, the literature suggests that male students are more overconfident, however, the gender difference in confidence can

[3] There are three key differences between Grimes (2002) and the present study. First, the present study collect students' grade expectations across a much longer time, which is important to explore the self-control related problems (e.g. students are much less likely to suffer from the self-control problems during the last 48 hours until exam). Second, the consumption and instrumental motives are indistinguishable in Grimes (2002) because of the short observation time and because students' expectations are not collected close to result realisation. Third, the drop in confidence after the exam in Grimes (2002) might be caused by students changing their perceptions about the difficulty of the exam. On the other hand, the present study excludes this possibility because essay questions are announced much earlier.

be task dependent.[4] Similarly in Nowell & Alston (2007), overconfident grade expectations are observed, and male students are more overconfident than female peers. In addition, they find that weak students with lower GPAs exhibit greater overconfidence than strong students. Students in lower division classes have a greater tendency to hold overconfident expectations than do those in upper division classes.

The phenomena that weak students are more overconfident has also been supported by several other studies (e.g. Sinkavich, 1995; Grimes, 2002; Edwards et al., 2003; Lindsey & Nagel, 2015). It is believed to be caused by the Dunning-Kruger effect that low-skilled students lack not only the content knowledge but also the metacognitive skills that would allow them to appreciate their lack of content knowledge (Kruger & Dunning, 1999). In other words, incompetent individuals often fail to know how deficient their performance is, and thus hold overconfident beliefs. Empirical evidence on the Dunning-Kruger effect is prevalent in the education literature (e.g. Dunning et al., 2003; Dunlosky & Metcalfe, 2008; Bell & Volckmann, 2011).[5] The observed overconfidence among students may be different across cultures. For example, although Americans and Western Europeans tend to believe themselves as above average along almost every desirable dimension, subjects from East Asia do not (Heine et al., 1999, 2001). Therefore, the generality of the overconfidence in education across cultures is not a given fact. Also, Dunning et al. (2004) argue that the presence of one aspect of overconfidence in one culture does not necessarily imply that people with such cultural background are overconfident in all aspects. For example, although Eastern subjects do not hold the above-average beliefs, studies suggest that Eastern students tend to be more overconfident about the accuracy of their judgments than American students (Yates et al., 1997).

Evidence suggests that students often lack the self-control ability to implement study plans. Duckworth & Seligman (2005) find that for adolescents, the de-

[4] A number of studies compare the behavioural differences between male and female in both math and word tasks. The main finding is that males are more confident when competing for math tasks, but not for word tasks (for a review see, Niederle & Vesterlund, 2011).

[5] It should also be noted that the existence of the Dunning-Kruger effect has been challenged by several studies, for example Burson et al. (2006) find that individuals across all ability levels have similar degrees of unawareness of their ability. Clayson (2005) argues that the student overconfidence is caused by a systematic effect relating to students past experience and expectations, not by the metacognitive effects of the Dunning-Kruger effect. Also, Krajc & Ortmann (2008) states that the fact that low-skilled individuals are more overconfident can be a result of "floor" effects. On the other hand, Schlösser et al. (2013) reply to the above challenges and confirm the overall validity of the Dunning-Kruger effect.

gree of self-discipline accounts for more than twice as much variance as IQ in many aspects of academic performance. Numerous empirical tests have been conducted and the correlation between the student's self-control ability and her academic success is robust (e.g., Allan & Lonigan, 2011; Véronneau et al., 2014; Duckworth & Carlson, 2015; Duckworth et al., 2016). These studies suggest that the lack of self-discipline is a major reason for students failing in academic challenges. Given the significant negative consequences of the self-control problem, behavioural economists argue that individuals who lack self-control may use commitment devices to pursue long-term goals. Examples of the commitment devices include self-imposed deadlines (Ariely & Wertenbroch, 2002), long-term membership contracts (DellaVigna & Malmendier, 2006), saving in the face of negative interest rate (Besley, 1995) and pre-purchased fertilizer coupons (Duflo et al., 2011). Bryan et al. (2010) summarise the commitment devices into two groups, hard commitments and soft commitments. Hard commitments involve real economic penalties for failure or rewards for success, on the other hand, soft commitments are motivated by psychological factors. Specifically, in the education context, a commonly used hard commitment is scholarships or other forms of financial support. However, the efficiency of imposing financial incentives on students is challenged by many studies.[6]

In Chapter 4 of this thesis, being overconfident about one's ability is proposed as a soft commitment device. In the present chapter, I aim to provide some supporting evidence. Another soft commitment, goal setting behaviour in education has been studied by many researchers. performance-based goal setting (e.g. a student self-initiate or set by teachers a goal on her exam performance) is commonly studied among education psychologists and a positive correlation between goal setting and academic performance is identified (e.g., Harackiewicz et al., 1997; Elliot & McGregor, 2001; Darnon et al., 2009). However, a recent study by D. Clark et al. (2017) finds that performance-based goals have positive but statistically insignificant effects on academic performance through a large scale field experiment. On the other hand, D. Clark et al. (2017) argue that task-based goals (e.g. a student who self-initiates or set by teachers a goal on how many course tasks to be completed) are much more effective than performance-based goals through the channel that task-based goals increase the completion of course tasks.

[6]Despite the fact that financial programs are costly, one key problem is that monetary rewards may crowd out the intrinsic incentives to study (Gneezy et al., 2011). Also, many studies suggest that the effect of such programs are insignificant (for a review, see Koch et al., 2015).

It should be noted that, apart from motivated overconfidence argument, the observed overconfident beliefs held by students might be potentially explained by other theories. Wishful thinking might be one reason why students hold unrealistic optimistic beliefs about their performance. Psychological studies commonly believe wishful thinking is the outcome of a conflict between a desire to have an accurate picture of the world an a desire to reach a 'directional' (often overoptimistic) conclusion (Kunda, 1990). Economists generally follow a similar approach, viewing wishful thinking as part of a strategy to balance the gain from positive feelings against the cost in biased decisions (Akerlof & Dickens, 1982; Brunnermeier & Parker, 2005). Mayraz (2011) finds evidence for wishful thinking in a lab and Serra & DeMarree (2016) argues that wishful thinking might be able to explain the overconfident grade forecasts reported by students. However, theories of wishful thinking are incapable to explain the time-varying perspective of our data.

Learning with new information might potentially explain the fact that students hold dynamic beliefs about their performance. If students do not have perfect information about the difficulty of the coursework nor their ability, they may initially hold inaccurate beliefs and update their beliefs with new information. For example in our case, through working on the essay, students may be better informed and adjust their beliefs about their performance. There are empirical evidence that students do not understand the marking system or do not know how to achieve a better academic outcome (e.g., Garner, 1990; D. Clark et al., 2017). There are also evidence that students might be able to adjust their expectations with new information. Magnus & Peresetsky (2017) found evidence that students, especially female students, were able to adjust their performance expectations on future exams according to their past exam results. Such learning story is unlikely to explain our data for two reasons. First, from the survey response, we do not find evidence that students believe that the difficulty of the coursework is increasing while working. Second, our data contradicts the existing empirical finding that female students learn more successfully than male students. Therefore in summary, the motivated overconfidence theory best explain our empirical observation.

5.3 Design of the Field Study

5.3.1 Description of the course and sample

The present field study was conducted at a leading research university in the UK. All students in this study were enrolled in a year-long either first or second year core economics course (Econ 1 and Econ 2, respectively). Both courses are worth 20 ECTS Credits[7], which is twice compared to a standard course. These courses are compulsory for economics students and they are required to achieve at least 50% to progress and are thus, the most important courses for year 1 and year 2 economics students. Both courses require students to submit a 1,500 words essay, and the essay mark is a significant component of their final grade. Participation in this study is completely voluntary, and we sought consent from all subjects before the start of the experiment. We employed a within-subjects design: subjects are asked to complete three online surveys at different points of time. Students are not informed the details of the following surveys. Three groups of students are invited: (1) Students taking the course Econ 1 in 2015-2016 academic year (henceforth, Econ1a); (2) Students taking the course Econ 2 in 2015-2016 academic year (henceforth, Econ2); (3) Students taking the course Econ 1 in 2016-2017 academic year (henceforth, Econ1b). Table 1 provides basic statistics about our subjects for each group.

5.3.2 Online Learning Platform

Our online surveys are conducted through the online learning platform, Blackboard Learn. Students are familiar with its interface and use this platform for most academic activities from downloading course materials to submitting essays/tests. I use this platform to conduct this online study mainly because it supports a within-subject survey design. As described in the following subsection, the study contains three surveys in total and Blackboard Learn makes it possible to identify the responses made by the same subjects.[8] In addition, performance data, such as tutorial attendance records and exam scores are also stored in this platform, which assists our analysis.[9] Furthermore, compared to standard classroom experiments, our online experiment ensures privacy and min-

[7] The corresponding total study hours, including lectures, tutorials and independent studies, are 400 hours.

[8] All the data presented to the author is completely anonymous, and the data collection process complied with university ethics policy.

[9] Consent from participants is collected with the approval from the ethics committee of the university.

imizes potential communication and the social pressure raised during standard classroom experiments.

5.3.3 The Surveys

Our experiment is made with a total of three online surveys, denoted as Survey 1, Survey 2 and Survey 3. Email invitations were sent to all students taking the corresponding course. The main question of interest is about their expectation on their essay performance. In addition, the surveys collected information related to essay performance, such as language and experience of essay writing were collected. Moreover, we asked questions related to their individual characteristics such as their self-control ability. The timing of the surveys are: the first survey is released three weeks prior to the essay deadline and is available for 7 days; the second survey is released just after the essay deadline and is available for 7 days; the third survey is released two days prior to the essay marks release and is available until essay marks release. The timing and availability of the surveys are presented in Figure 5.1.

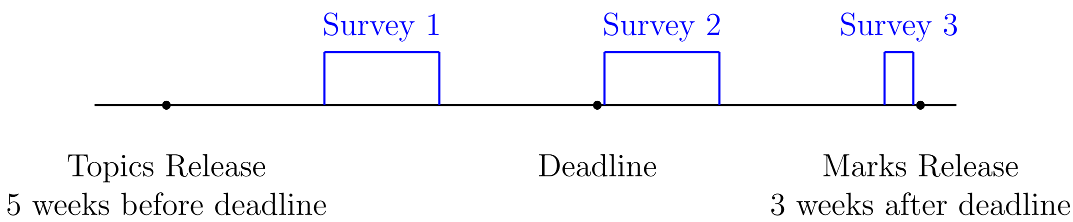

Figure 5.1: Timeline and Availability of the Surveys

Note: The blue rectangles represent the starting and finishing dates of the surveys.

Printing credits and Amazon vouchers were provided as incentives for participation. Two slightly different types of incentives are provided. For Econ1a and Econ2 (academic year 2015-2016) students, they were promised to share a total of 40 £10 printing credits and 5 £50 Amazon vouchers. For Econ1b (academic year 2016-2017) students, they were promised to get £5 printing credit for sure if they complete all three surveys and enter a draw for 1 £50 Amazon voucher. As Table 5.1 suggests, providing certain rewards might be better at motivating students for participation. Participates are informed that the compensation they receive depends exclusively on completion and does not depend on the responses they submit. The reason not to provide incentives for accurate expectation is that students can be both conscious and unconscious about the belief distortion due to instrumental and consumption motives (Burks et al., 2013; Bénabou & Tirole, 2016). If financial incentives are provided for accurate beliefs, students who are conscious of the fact that they hold inflated beliefs may have incentives to submit a lower response, yet still adopt inflated beliefs as motivation or consumption. In other words, if such incentives were provided, we would only observe the cognitive distortions possessed by unconscious students.[10]

Table 5.1 presents a summary of the number of participants. The fraction of students who complete all three surveys is not high since the third survey was available for a short time only and voluntary participation is emphasised. Therefore, in order to utilise the most of the observations, students who complete two surveys are also included in the analysis when it is possible.[11]

	All	**Econ1a**	**Econ1b**	**Econ2**
Total No. of students	1,034	360	386	288
Students complete at least one survey	441	143	184	114
Students complete all three surveys	150	34	82	34

Table 5.1: Number of Participants

5.4 Theoretical Prediction

The structure of the present online experiment follows closely to the motivated overconfidence theory proposed in Chapter 4. Consistent with chapter 4, I denote the expectations about their essay performance at survey 1, 2 and 3 as X_1, X_2, X_3 respectively. Table 5.2 summaries the main theoretical predictions. Details are presented in Chapter 4. Based on the theory, I list three main hypotheses of interest, and these hypotheses are tested in the next section.

Hypothesis 1. $X_2 > X_3$. *Subjects' expectations are affected by the consumption motive.*

Hypothesis 2. $X_1 > X_2$. *Subjects' expectations are affected by the instrumental motive.*

Hypothesis 3. D_1 is negatively correlated with Self-control problem. *Subjects with lower self-control ability inflate their beliefs to a greater extent while working.*

[10] Indeed, providing financial incentives for accurate grade expectation can potentially be an interesting extension to study whether overconfident students are aware of their optimism.

[11] Appendix B reports the behaviour of these 150 students who complete all three surveys.

	Overconfidence			Dynamics
	$\boldsymbol{X_1}$	$\boldsymbol{X_2}$	$\boldsymbol{X_3}$	
No motives	No	No	No	$X_1 = X_2 = X_3$
Consumption only	Yes	Yes	No	$X_1 > X_2 > X_3$
Instrumental only	Yes	No	No	$X_1 > X_2 = X_3$
Both motives	Yes	Yes	No	$X_1 >> X_2 > X_3$

Table 5.2: Theoretical Predictions

Note: $X_1 >> X_2 > X_3$ stands for the fact that if both consumption and instrumental motives present, the theory predicts a significant decrease from X_1 to X_2, while a smaller drop from X_2 to X_3.

5.5 Results

The main purpose of this paper is to test the theory of consumption and instrumental motives of confidence. Specifically, it addresses the following two questions. Does the data support the existence of a consumption motive or an instrumental motive or both? Does the data help to reject alternative stories? A number of hypotheses are proposed to answer these two main questions. In this section, I first describe the main descriptive statistics of the data. Then, statistical tests results are presented, and the hypotheses are examined.

5.5.1 Descriptive Statistics

Table 5.3 and Figure 5.2 present the descriptive statistics on the expectations that students submit in three surveys. First of all, in contrast to most earlier studies, students in this study do not overestimate their essay grade even when they are most optimistic. Second, students are most confident while working on their essay, become less confident after submission and continuing holding such level of confidence till result realisation. Therefore, students seem to hold a dynamic view about their essay performance, and the same pattern applies to all three samples.

5.5.2 Main Findings

The first question to investigate is whether students in our sample inflate their expectations for the savouring purpose. As presented in Table 5.2, if the consumption motive presents, students hold a higher expectation at the time of survey 2 than survey 3 since there is no time for savouring at the time of survey 3. The summary statistics table and figure above suggest that $X2 \approx X3$, statistical tests and detailed within-subject scatter plots further confirm that there is no statis-

	X_1	X_2	X_3	Real Score (N=150)	Real Score (all students)
Econ1a	65.41	63.11	63.82	64.94	61.44
Econ1b	62.88	59.99	59.65	63.45	61.53
Econ2	60.68	57.44	57.53	60.68	59.63
Total	62.95	60.12	60.11	63.16	60.94

Table 5.3: Summary Statistics Table

Note: Scores are percentage grades using the system that is common among UK universities: <40, Fail; 40-49, D; 50-59, C; 60-69, B; >70, A. Typically, the mean and median marks are close to each other and are between 55 and 65.
The first four columns, (X_1, X_2, X_3 and Real Score (N=150)), are based on the data of the 150 students who complete all three surveys. The last column presents the average real score of all students who submitted the essay. Students who complete all three surveys have a better real score on average. Details can be found in Table 5A.7 in Appendix A.

tical difference between $X2$ and X_3. In other words, the data in this study does not support the presence of the consumption motive of overconfidence.

Table 5.4 shows that, at the aggregate level, there is no statistical difference between X_2 and X_3 for each three individual samples and the aggregate. Non-parametric statistical results based on 173 subjects who complete both survey 1 and survey 2 suggest that the mean of X_2 and X_2 are of no difference.[12] Similar results are presented at the individual level in Figure 5.3. In this figure, the location of each scatter point represents one subject's submitted expectations in survey 2 and survey 3. Specifically, the vertical axis stands for X_2 and the horizontal axis represents for X_3. Therefore, if the consumption motive presents and thus $X_2 > X_3$, these scatter points should be, on average, located above the 45 ° line. On the other hand, the data shows that the scatter points are located around the 45 ° line. In other words, students do not hold higher expectations in survey 2 compared to survey 3. Therefore, the data does not support the existence of the consumption motive and Hypothesis 1 is rejected.

	$H_1 : X_2 > X_3$			
	Wilcoxon signed-rank	**Sign ($X_2 > X_3$)**	**Sign ($X_2 \neq X_3$)**	**N**
Econ1a	0.09*	0.98	0.11	41
Econ1b	0.81	0.56	>0.99	87
Econ2	0.99	0.50	>0.99	45
Total	0.81	0.82	0.47	173

Table 5.4: H_1: Tests of the Consumption Motive

Note: p-values are reported for each test. $p < 0.1$, *; $p < 0.05$, **; $p < 0.01$, ***

Finding 1. Hypothesis 1 is rejected and no consumption motive is identified.

[12]For Econ1a students, it is marginally significant that $X_3 > X_2$.

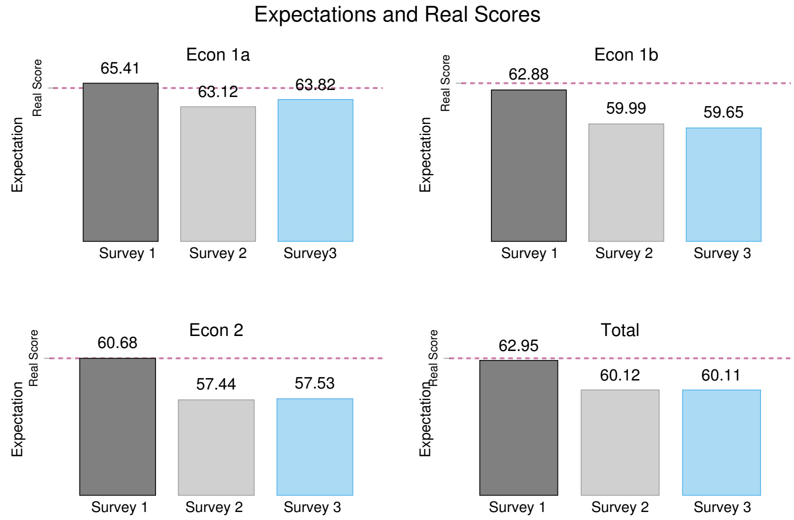

Figure 5.2: Graphical Summary Statistics

Note: The horizontal red dashed lines stand for the average real scores. The bars represent the students' expectations at each point of time. Specifically, the dark grey, light grey and light blue bars represent the level of expectations at survey 1, survey 2 and survey 3 respectively. Total number of subjects, N=150.

The motivated overconfidence theory suggests that the instrumental effect of overconfidence helps individuals to exert more effort while working. Specifically in this study, if students distort their beliefs due to instrumental reasons, $X_1 > X_2$.[13] Table 5.5 indicates that at the aggregate level, X_1 is significantly higher than X_2 for all three samples and the aggregate. Figure 5.4 confirms the finding that $X_1 > X_2$ from the individual perspective. In this scatter plot, it can be observed that more points are located above the 45° line. Thus more students hold inflated beliefs while working on the essay and many of them adjust their expectations downwards significantly after submission. The result that $X_1 > X_2$ suggests a possibility that students adopt inflated beliefs for motivation.

Finding 2. Hypothesis 2 is not rejected and instrumental motive is likely to be effective.

A further investigation about the presence of the instrumental motive is through the lens of the self-control problem. As predicted by the theory, the instrumental motive is adopted as a commitment device to deal with the self-control problem,

[13]Theoretically, the gap between X_1 and X_2 is caused by both the withdraw of the instrumental motive and the decrease in the consumption motive. However, given the data strongly rejects the existence of the consumption motive, the difference between X_1 and X_2 is likely to be driven exclusively by the instrumental motive.

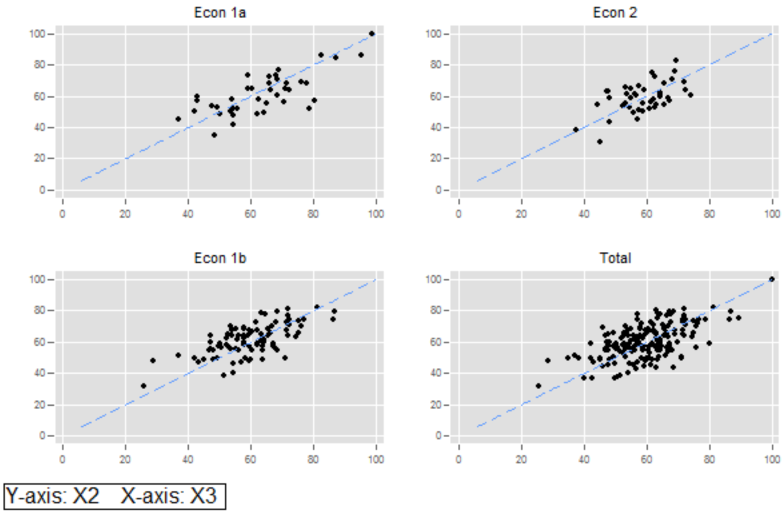

Figure 5.3: H_1: Scatter Plots of X_2 and X_3

Note: The vertical axis stands for the value of the students' expectation at survey 2 (X_2) and the horizontal axis for survey 3 (X_3) . The blue dashed line is the 45° line. The locations of the scatter points are slightly jittered to present the distribution density.

	$H_2 : X_1 > X_2$			
	Wilcoxon signed-rank	**Sign** ($X_1 > X_2$)	**Sign** ($X_1 \neq X_2$)	**N**
Econ1a	0.02**	<0.01***	<0.01***	51
Econ1b	<0.01***	<0.01***	<0.01***	101
Econ2	<0.01***	<0.01***	<0.01***	47
Total	<0.01***	<0.01***	<0.01***	199

Note: p-values are reported for each test. $p < 0.1$, *; $p < 0.05$, **; $p < 0.01$, ***.

Table 5.5: H_2: Tests of the Instrumental Motive

and in equilibrium, the extent of belief inflation is negatively correlated with the individual's self-control ability because individuals with high self-control ability do not need much belief inflation to exert the optimal level of effort. Clearly, if a student has perfect self-discipline (and thus does not suffer from present bias), she has no incentive to adopt any commitment devices. Therefore, if the drop between X_1 and X_2 is due to the disappearance of the instrumental motive, we should be able to observe that students with lower self-control abilities adjust their beliefs downward to a greater extent.

Let $D_1 = X_1 - X_2$ be the drop of confidence after submission. Figure 5.5 presents the distribution of D_1, and it is clear that for all samples, students on average adjust their expectations downwards after submission. Specifically for the aggregate sample (N=199), 27.6% of the students report the same level of expectations in

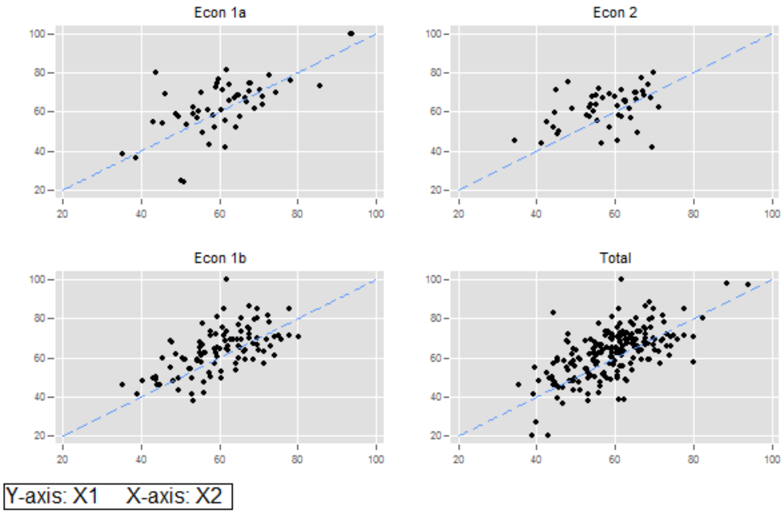

Figure 5.4: H_2: Scatter Plots of X_1 and X_2

Note: The vertical axis stands for the value of the students' expectation at survey 1 (X_1) and the horizontal axis for survey 2 (X_2) . The blue dashed line is the 45° line. The locations of the scatter points are slightly jittered to present the distribution density.

survey 1 and survey 2; 54.3% of the students submit lower expectations in survey 2 than in survey 1, and the remaining 18.1% of the subjects become more confident after the submission. To test whether D_1 is correlated with the degree of the self-control problem, survey 2 incorporates questions about their desired level of effort and their actual level of effort.[14] Thus, the self-reported degree of self-control problem (SCP) is defined as the difference between the planned total hours and the actual hours working on the essay ($SCP = hour\ planned\ - hour\ worked$). Regression results from Table 5.6 suggest a significant positive correlation between the drop of confidence after submission and the degree of the self-control problem. In other words, the data supports a possibility that the instrumental motive is more likely to be adopted by students with greater self-control problems as a commitment device.

Table 5.6 reports OLS regressions of the difference between X_1 and X_2 on students characteristics and their self-reported degree of self-control. In the first column, student characteristics including gender and exam performance[15] are regressed. The result suggests that female students change their beliefs significantly

[14] The level of effort is measured in terms of time (how many hours are spent on working on the essay).

[15] Students taking Econ 1 and Econ 2 are required to take one mid-term exam and one class exam prior to the coursework essay period. These two exams contribute to their final grade and the variable "Exam Performance" is the average of these two exams.

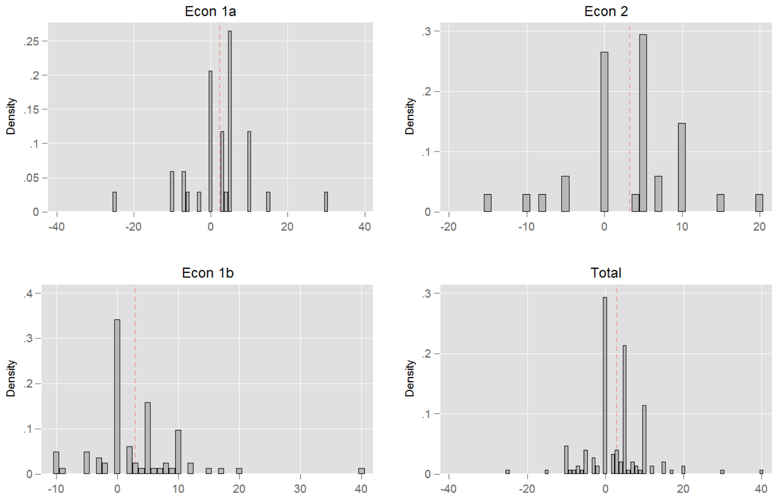

Figure 5.5: H_3: Histogram of the Decrease in Expectations

Note: The vertical axis stands for the density of the distribution and the horizontal axis is D_1, the difference between X_1 and X_2. The vertical dashed indicates the mean of the distribution.

less before/after submission. Since evidence on gender differences in education indicates that females have better self-control abilities (e.g. Duckworth & Seligman, 2006), female students may be less incentivised to adopt the inflated beliefs as a commitment device and thus do not adjust their expectations as much as their male peers. In the second column, an additional variable about the student's self-control ability is introduced. The result suggests that students with a greater degree of self-control problem inflate their expectations more while working. Such finding is consistent with the theoretical prediction that individuals with self-control problems inflate their expectations while working to deal with the present temptations. Column three and four provide further evidence on the correlation between the expectation gap and the self-control problem for each gender. Results indicate that the correlation is valid for both male and female students.

Finding 3. Hypothesis 3 is not rejected, and students with greater self-control problem inflate their expectations more while working.

Dependent Variable: D_1				
	(1) Total	(2) Total	(3) Male	(4) Female
DFemale	-3.04***	-2.49**		
	(1.06)	(1.07)		
Exam Performance	-0.02	0.00	-0.06	0.08
	(0.04)	(0.04)	(0.05)	(0.05)
DEcon 2	2.47	2.04	0.99	2.61
	(1.54)	(1.53)	(2.24)	(2.08)
DEcon 1b	0.97	0.45	-0.52	1.66
	(1.29)	(1.29)	(1.79)	(1.84)
Self-control Problem		1.02***	1.10*	0.88*
		(0.38)	(0.59)	(0.50)
Constant	4.22*	1.97	6.53*	-5.40*
	(2.31)	(2.43)	(3.49)	(3.17)
Observations	195	194	102	92

Table 5.6: Determinants of the Confidence Drop

Note: Variables starts with "D" are dummy variables. DFemale with base male students being 0. DEcon 2 and DEcon 1b are student samples with base sample Econ 1a being 0.
Among the 195 students who submitted expectations in survey 1 and survey 2, one subject did not answer the self-control questions and thus excluded from regression (2).
OLS regressions standard errors are reported in the brackets. $p < 0.1$, *; $p < 0.05$, **; $p < 0.01$, ***.

5.6 Discussion

Several alternative hypotheses seem to be convincing at explaining the data of this study. In this section, I explain why these alternative explanations are unlikely to be valid.

5.6.1 Learning

An alternative argument regarding the drop in expectation after submission is that students may have learned new information during this period. Students may adjust their expectations based on new information about the task or signals affecting their metacognition.[16] Although it is difficult to rule out these learning effects completely, a number of reasons below suggest that learning may not play a key role in the drop in expectations before/after submission.

The nature of the essay-writing task prohibits excessive learning during the writ-

[16]For example, students may find fault in their submitted work while communicating with other students and become less confident. Alternatively, they may adjust their expectation downwards simply because they realise that they have imperfect self-control ability (and thus work less than expected).

ing period. The essay questions do not have clear-cut right or wrong answers, and students are less likely to update from social learning as it is difficult to assess the quality of one's essay. In comparison, many exam questions have a simple model answer, which makes students much easier to learn by themselves or from communicating with their peers. In addition, there is no uncertainty about the questions and thus no surprise for students. The essay topic is certain and students can choose the one they are more familiar with. On the other hand, the pre/post exam confidence dynamics observed by earlier studies are likely to be a result of learning.[17] Furthermore, the essay task provides little feedback until result realisation. In contrast to an exam for which students often get adequate feedback from quiz and textbooks, almost no official feedback is available until the result realisation. Students submit their work by sending their files online and no feedback of any form is generated after submission.

The data in the present study contradicts the findings on the persistence of expectations with learning. A large number of studies on grade expectations suggest that students do not adjust their expectations with respect to new information (e.g. Murstein, 1965; Serra & DeMarree, 2016; Foster et al., 2017), which indicates the drop in expectation may not be a result of learning. Also, a few studies report that women tend to be more flexible in revising their expectations with more experience (e.g. Grimes, 2002; Magnus & Peresetsky, 2017). However, in the present study, males are much more flexible in terms of adjusting grade expectations.

The naivety about one's self-control ability is unlikely to explain the present data. A slightly alternative learning argument may argue that students decrease their expectation because they learned the fact that they suffer from the present temptation. In other words, students are naive about their self-discipline at the beginning of the task and eventually learn the fact. Given the fact that Econ 2 students all have completed Econ 1, if the naivety and learning argument is valid, Econ 2 students should be less naive compared with Econ 1 students due to additional experience. Consequently, Econ 2 students should reduce their expectations less than Econ 1 students. However, in the data, Econ 2 students on average adjust their expectations more than Econ 1 students.[18]

[17]Students after taking exams may update their grade expectations because the questions are different from her expectation. Examples include "I didn't expect this type of questions", "The questions are (not) what I've prepared".

[18]The average gap (D_1) for Econ 1 students is 2.63 and for Econ 2 students is 3.66. The difference in the gap between Econ 1 and Econ 2 is not significant (Wilcoxon-Mann-Whitney and Kolmogorov-Smirnov).

5.6.2 Inexperience and the Perception of Difficulty

As presented in Figure 5.2, Econ 2 students (with more experience) on average adjust their beliefs to a greater extent. The perception of the difficulty of the task is collected in the survey. Specifically, the question asks if students feel the difficulty of the essay changes over time. Among the 118 students who complete this question[19], 28.0% of the subjects feel that the essay is getting more difficult while working; 21.2% believe the essay becomes easier and the remaining 50.9% do not hold dynamic perceptions of the difficulty of the task. Therefore, the change in expectations is unlikely to be caused by the change in the perception of difficulty. Table A shows that students who complete all three surveys have a better academic performance than others.

5.7 Conclusion

This paper empirically tests whether overconfidence is driven by consumption and instrumental motives. By collecting students' grade forecasts at different points of time, this design allows me to disentangle these two motives. The findings suggest that, in order to deal with present temptation, students are likely to adopt an inflated belief while working. On the other hand, overconfidence does not present during the waiting period, and it indicates that the consumption motive is unlikely to be effective. To the best of my knowledge, this paper presents the first experimental support for the instrumental argument of overconfidence. Consistent with the theory, female students and those with better self-control abilities inflate their beliefs less while working.

One limitation of this study is that I cannot tell to what extent the inflated beliefs are effective at motivating students. It is difficult to compare the level of effort with/without belief distortion for the same subject. Also, the data cannot explain exactly why some students do not adopt inflated beliefs. It might just because those students have enough self-control ability or are realistic. Alternatively, those who do not distort beliefs may not be aware of the existence of such commitment device. The finding that second year students have a larger decrease in expectations after submission might suggest that some students are learning with experience to adopt inflated beliefs as a commitment tool. Psychologists have found that self-efficacy training is indeed helpful in a number of situations including working performance and disease fighting (e.g. Gist et al., 1989; Eden & Aviram, 1993; Stajkovic & Luthans, 1998). Thus, students might learn to be

[19] This question is only available to Econ 1b students.

overconfident for the instrumental purpose.

The findings of this paper are in line with the general argument that people can manipulate their beliefs for a purpose. Recent biological findings on the "open-label placebo effect" suggest that patients report better feelings by taking ineffective placebos (e.g. sugar pills) knowing what they really are (e.g. Berry-Kravis et al., 2009; Kelley et al., 2012). These results indicate a paradoxical result. On the one hand, people are successful at manipulating their beliefs (e.g. reality denial) to improve welfare. On the contrary, it seems that cognitive distortions are heavily constrained, and have to be triggered by a sense of ceremony or licensing.[20] Future research in decision science should address the effectiveness and limitations of motivated beliefs.

[20]Perhaps goal setting in education works as the open-label sugar pills for students with self-control problem. Setting a goal makes students feel ceremonial, and helps to trigger the motivated overconfidence.

Appendices

A Selection Bias

In this section, I show that students who complete all three surveys on average have better academic performance than the rest. It is not surprising since weak students who seldom check the university email or learning materials are unlikely to participate in the surveys available online. Also, the slightly better than average sample in this study turns out to be better suited in the question I study. The instrumental and consumption motives come into effect only if the students care about their study. Clearly the sample in this study is highly motivated students who care about their grades, and may engage in cognitive distortions.

	$H_2 : X_1 > X2$					
	GPA			**Real Score**		
	All-complete	**Rest of the class**	**p**	**All-complete**	**Rest of the class**	**p**
Econ 1a	57.07 (N=34)	49.96 (N=267)	<0.01 ***	64.94 (N=34)	61.01 (N=285)	0.01**
Econ 1b	57.65 (N=82)	50.41 (N=271)	<0.01 ***	63.45 (N=82)	60.96 (N=273)	0.02**
Econ 2	66.29 (N=34)	59.66 (N=244)	0.04**	60.67 (N=34)	59.48 (N=245)	0.62
Total	59.48 (N=150)	53.14 (N=782)	<0.01 ***	63.16 (N=150)	60.53 (N=803)	<0.01 ***

Table 5A.7: Summary of Selection Bias

Note: The p-values are reported for two sided WilcoxonMannWhitney test. $p < 0.1$, *; $p < 0.05$, **; $p < 0.01$, ***.

B Analysis with Students Complete All Surveys

In this section of the Appendix, I replicate the analysis in the main text by examining only students who complete all three surveys (fully-completed participants). Therefore for all descriptive statistics and regression results, the total No. of subjects is 150. All tables and figures in the main text are replicated in the same order. In sum, most results are consistent with the analysis of the all-available participants data, with the exception of the relationship between self-reported self-control problem and the attendance record. For the empirical result from all available participants, there exists a significant negative correlation between the self-reported degree of self-control problem and the tutorial attendance. However, such correlation is not identified with fully-completed participants.

The Hypothesis 1 is also rejected with fully-completed participants only. This result is consistent with the analysis with all-available participants.

The Hypothesis 2 is not rejected with fully-completed participants only. This result is consistent with the analysis with all-available participants. Specifically

	$H_1 : X_2 > X_3$			
	Wilcoxon signed-rank	**Sign** ($X_2 > X_3$)	**Sign** ($X_2 \neq X_3$)	**N**
Econ1a	0.31	0.92	0.36	34
Econ1b	0.68	0.50	>0.99	82
Econ2	0.94	0.58	>0.99	34
Total	0.81	0.71	0.74	150

Table 5A.8: Tests of X_2 and X_3 (cf. Table 5.4)

Note: With fully-completed participants only (N=150). p-values are reported for each test. $p < 0.1$, *; $p < 0.05$, **; $p < 0.01$, ***.

for the aggregate sample of fully-completed sample, 29.3% of the students report the same level of expectations in survey 1 and survey 2; 53.3% of the students submit lower expectations in survey 2 than in survey 1 and the remaining 17.3% of the subjects become more confident after the submission.

	$H_2 : X_1 > X_2$			
	Wilcoxon signed-rank	**Sign** ($X_1 > X_2$)	**Sign** ($X_1 \neq X_2$)	**N**
Econ1a	0.05*	<0.01***	0.02**	34
Econ1b	<0.01***	<0.01***	<0.01***	34
Econ2	<0.01***	<0.01***	<0.01***	82
Total	<0.01***	<0.01***	<0.01***	150

Table 5A.9: Tests of the Instrumental Motive (cf. Table 5.5)

Note :With fully-completed participants only (N=150). p-values are reported for each test. $p < 0.1$, *; $p < 0.05$, **; $p < 0.01$, ***.

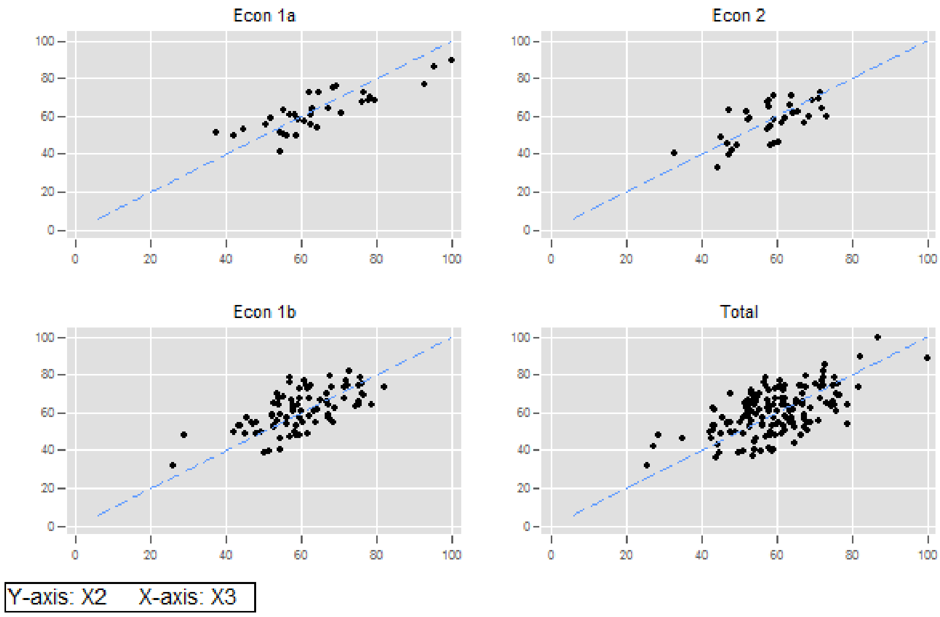

Figure 5A.1: Scatter Plots of X_2 and X_3 (cf. Figure 5.3)

Note: With fully-completed participants only (N=150). The vertical axis stands for the value of the students' expectation at survey 2 (X_2) and the horizontal axis for survey 3 (X_3) . The blue dashed line is the 45° line. The location of the scatter points are slightly jittered to present the distribution density.

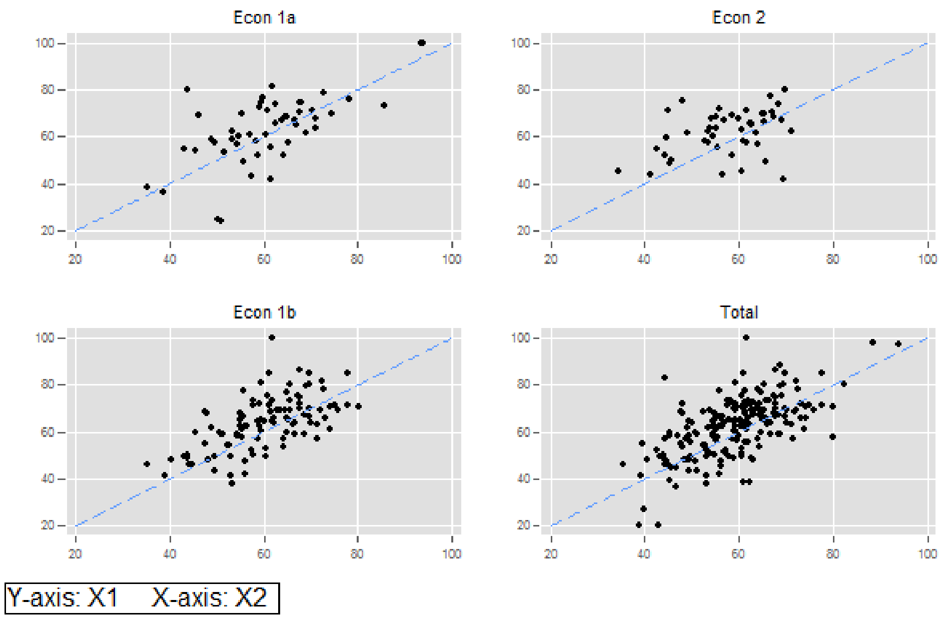

Figure 5A.2: Scatter Plots of X_1 and X_2 (cf. Figure 5.4)

Note: With fully-completed participants only (N=150). The vertical axis stands for the value of the students' expectation at survey 1 (X_1) and the horizontal axis for survey 2 (X_2) . The blue dashed line is the 45° line. The location of the scatter points are slightly jittered to present the distribution density.

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